

NATURAL LANGUAGE PROCESSING IN HEALTHCARE INFORMATICS

CHALLENGES AND FUTURE DIRECTIONS



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Natural Language Processing in Healthcare Informatics: Challenges and Future Directions

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CONTENTS

FOREWORD	i
PREFACE	ii
LIST OF CONTRIBUTORS	iv
CHAPTER 1 INTRODUCTION TO ARTIFICIAL INTELLIGENCE AND NATURAL LANGUAGE PROCESSING IN HEALTHCARE	1
<i>T. Sayamsmruti Panda, Saranya Jayapalan, A. Shankar and Basant K. Tiwary</i>	
INTRODUCTION	2
Computational Advances in Clinical Practices	4
Remote Patient Monitoring and Telehealth	4
<i>AI-Powered Wearables and Sensors</i>	4
<i>AI in Heart Monitoring</i>	4
<i>AI in Predicting Women's Fertility</i>	5
<i>AI Wearables for the Blind and Visually Impaired</i>	5
<i>Robotic Surgery and AI-Powered Surgical Robots</i>	6
FDA-Approved AI-driven Healthcare Devices	6
LumineticsCore	6
NATURAL LANGUAGE PROCESSING (NLP) IN HEALTHCARE	7
Definition and Overview	7
NLP Techniques in Healthcare	7
<i>Text Mining</i>	7
<i>Information Extraction</i>	8
<i>Question Answering</i>	8
<i>Machine Translation</i>	9
<i>Sentiment Analysis</i>	9
APPLICATIONS OF NLP IN HEALTHCARE	10
Electronic Health Record (EHR) Analysis	10
Clinical Decision Support	11
Medical Literature Mining	11
Patient-Provider Communication	12
Role of Artificial Intelligence in Medical Imaging Research	12
Revolutionizing Image Analysis and Diagnosis	12
Enhancing Efficiency and Reducing Errors	13
Applications in Personalized Medicine	13
Supporting Remote and Resource-Limited Settings	13
CONCLUSION	14
ACKNOWLEDGEMENT	14
REFERENCES	14
CHAPTER 2 CHALLENGES IN NATURAL LANGUAGE PROCESSING FOR HEALTHCARE INFORMATICS	20
<i>R. Brindha, R. Elanthirayan, R. K. Pongiannan, Bharath Addepalli, K. Kyathisree, T. Y. S. Srihari and M. Harini Reddy</i>	
INTRODUCTION	20
Background on NLP and Healthcare Informatics	23
Overview of NLP Technologies	24
Key Healthcare Informatics Concepts	25
Historical Context and Evolution of NLP in Healthcare	26
DATA CHALLENGES	27

Data Quality and Standardization	27
<i>Inconsistencies in Medical Terminologies</i>	27
<i>Variability in Data Sources</i>	28
Data Privacy and Security	29
<i>Regulatory Requirements</i>	29
<i>Anonymization and De-Identification Challenges</i>	29
Data Availability	30
<i>Limited Access to Large, Annotated Datasets</i>	31
<i>Issues with Data Sharing and Integration:</i>	31
LINGUISTIC CHALLENGES	31
Domain-Specific Language	32
<i>Specialized Medical Terminology and Jargon</i>	33
<i>Variability in Language Use Among Different Specialties</i>	33
Ambiguity and Polysemy	33
<i>Challenges with Ambiguous Terms and Phrases</i>	33
<i>Contextual Understanding in Medical Texts</i>	34
Language Variability	34
<i>Multilingual and Multicultural Issues</i>	34
<i>Variations in Language Use Across Regions and Populations</i>	35
COMPUTATIONAL CHALLENGES	35
Model Training and Evaluation	35
<i>Limitations of Existing Models for specific Medical Tasks</i>	36
<i>Challenges in Evaluating Model Performance in Healthcare</i>	36
Scalability and Efficiency	37
<i>Resource-Intensive Nature of NLP Models</i>	37
<i>Computational Requirements and Optimization</i>	38
Integration with Existing Systems	39
<i>Challenges in Incorporating NLP Solutions into Clinical Workflows</i>	39
<i>Interoperability with Other Healthcare Technologies</i>	41
ETHICAL AND SOCIAL IMPLICATIONS	42
Bias and Fairness	42
<i>Risks of Biased Outcomes in NLP applications</i>	42
<i>Impact on Diverse Patient Populations</i>	43
Transparency and Explainability	44
<i>Need for Interpretability of NLP Systems in Healthcare</i>	44
<i>Balancing Automation with Human Oversight</i>	44
Impact on Healthcare Professionals	45
<i>Effects on Clinical Decision-Making</i>	45
<i>Potential Shifts in Job Roles and Responsibilities</i>	46
CASE STUDIES	47
NLP in Clinical Documentation	47
<i>Example of NLP Systems for Transcribing and Interpreting Clinical Notes</i>	47
Features	48
Advantages	48
NLP for Patient-Provider Communication	48
<i>Use Cases of Chatbots and Virtual Assistants in Healthcare Settings</i>	48
Qualities	48
Advantages	49
NLP in Medical Research	49
<i>Applications in Analyzing Scientific Literature and Research Data</i>	49
Applications	49

Advantages	49
FUTURE DIRECTIONS AND RESEARCH OPPORTUNITIES	50
Emerging Trends and Technologies in NLP	50
<i>Advances in Deep Learning and Transformer Models</i>	50
<i>Integration of Multimodal Data</i>	50
<i>Explainable AI (XAI) and Trustworthy NLP</i>	50
Potential Areas for Further Research	51
<i>Handling Bias and Ensuring Fairness</i>	51
<i>Enhancing Contextual Understanding</i>	51
<i>Personalization and Adaptability</i>	51
Collaborations Between NLP Researchers and Healthcare Professionals	51
<i>Interdisciplinary Research Teams</i>	51
<i>Shared Datasets and Open Research</i>	52
<i>Continuous Education and Training</i>	52
CONCLUSION	52
REFERENCES	52
CHAPTER 3 DEEP LEARNING TECHNIQUES FOR MEDICAL TEXT ANALYSIS	54
<i>L. Sankar Ganesh and P. Mohan Kumar</i>	
INTRODUCTION	54
Background	55
<i>Natural Language Processing in Healthcare</i>	55
<i>Deep Learning Approaches</i>	55
Deep Learning Techniques for Medical Text Analysis	56
<i>Recurrent Neural Networks</i>	56
<i>Convolutional Neural Networks</i>	58
<i>Transformer Model</i>	59
<i>Datasets</i>	60
Experimental Setup	61
<i>Preprocessing</i>	61
<i>Model Architectures</i>	61
<i>Findings from the Experiment</i>	62
<i>Applications of NLP in Healthcare</i>	64
DISCUSSION	65
Obstacles in Applying Deep Learning to Medical Text Processing	66
<i>A. Lack of Data and Annotation</i>	66
<i>B. Interpretability</i>	66
<i>C. Privacy and Ethical Concerns</i>	66
CONCLUSION	66
REFERENCES	67
CHAPTER 4 DATA PREPROCESSING AND ANNOTATION FOR NLP IN HEALTHCARE	70
<i>N. Priyadharshini, R. Nallakumar and G. Sekar</i>	
INTRODUCTION	70
Importance of Data Preprocessing in Healthcare NLP	72
TEXT CLEANING	72
Tokenization	72
Lemmatization and Stemming	72
Annotation in Healthcare NLP	73
Named Entity Recognition (NER)	73
Relation Extraction	74
Techniques and Challenges in Data Annotation	74

Manual vs. Automated Annotation	74
Inter-Annotator Agreement	74
Data Preprocessing Techniques for Model Improvement	75
<i>Stop-Word Removal</i>	75
<i>Vectorization</i>	75
Privacy and Ethical Considerations in Healthcare Data Preprocessing	75
Evaluation Metrics for Preprocessing and Annotation Quality	76
Preprocessing Evaluation Metrics	76
ANNOTATION QUALITY METRICS	76
CONCLUSION	77
REFERENCES	78
CHAPTER 5 EVALUATING LARGE LANGUAGE MODELS FOR RNA INTERACTION EXTRACTION: A COMPARATIVE STUDY ON BIOMEDICAL RESEARCH	80
<i>Balu Bhasuran, Forhan Bin Emdad and Mohammad Ishtiaque Rahman</i>	
INTRODUCTION	80
MATERIALS AND METHODS	82
LARGE LANGUAGE MODELS	83
The LLMs used in this study were:	83
MODEL CONFIGURATION AND TRAINING	83
EVALUATION METRICS	83
COMPARATIVE ANALYSIS	84
RESULTS	84
DISCUSSION	90
CONCLUSION	91
CONSENT FOR PUBLICATION	91
CONFLICT OF INTEREST	92
ACKNOWLEDGEMENT	92
REFERENCES	92
CHAPTER 6 FUTURISTIC APPROACH FOR ENHANCING HEALTHCARE USING BI- LSTM AND NLP	95
<i>R. Deepalakshmi and S. Mary Praveena</i>	
INTRODUCTION	95
LITERATURE REVIEW AND EXISTING MODEL	98
Bi-LSTM in Natural Language Processing (NLP)	98
Bi-LSTM in Time-Series Analysis	98
Speech Recognition and Audio Processing	99
Bi-LSTM in Machine Translation and Cross-Lingual Tasks	99
PROPOSED MODEL	100
Bi-LSTM Algorithm and Approach	100
Workflow of the Bi-LSTM	102
<i>Data Preprocessing</i>	102
<i>Model Architecture</i>	102
<i>Training the Model</i>	102
<i>Model Evaluation and Analysis</i>	103
Key Advantages of Bi-LSTM	103
Algorithm and Coding using MATLAB:	104
Algorithm and Coding using Python:	109
Observations	116
Interpretation of Classifier Performance	118
CONCLUSION	118

CONSENT FOR PUBLICATION	119
CONFLICT OF INTEREST	119
ACKNOWLEDGEMENT	119
REFERENCES	119
CHAPTER 7 ROLE OF KNOWLEDGE GRAPH IN RARE DISEASE PREDICTION	122
<i>Sabenabanu Abdulkadhar, Gurusamy Murugesan and Yasmin Abdulkadhar</i>	
INTRODUCTION	122
Biomedical Resources/Corpora and Databases	124
Architecture of Rare Disease Knowledge Discovery Process	127
Information Extraction	129
<i>Named Entity Recognition</i>	129
<i>Bio-Relation or Event Extraction</i>	129
<i>Knowledge Discovery Process by Network and Pathway Curation</i>	129
<i>Drug Targets Extraction</i>	130
<i>Postprocessing</i>	130
<i>Visualization of Rare Disease Knowledge Graph</i>	130
<i>Evaluation Metrics</i>	131
<i>Rare Disease Knowledge Discovery Process Approaches</i>	131
<i>NER Approaches</i>	132
<i>Relation Extraction and Knowledge Discovery Approaches</i>	133
CONCLUSION	134
REFERENCES	134
CHAPTER 8 LEVERAGING AI AND ML TO ENHANCE FOCUSED ULTRASOUND TREATMENTS FOR ESSENTIAL TREMORS	144
<i>Tamilalagan S., R. K. Pongiannan, R. Brindha, Jishnu K. S., Shijukumar K, K. P. Naveen and Telugu Maddileti</i>	
INTRODUCTION	145
RELATED WORKS	145
BACKGROUND	148
Role of ML and AI in the Treatment of Essential Tremor	150
PATIENT SELECTION AND STRATIFICATION	152
Treatment Plans	153
Real-time Monitoring	154
Post-Treatment Analysis	154
Improving with Feedback from Patients	155
CONCLUSION	156
REFERENCES	156
CHAPTER 9 A MATHEMATICAL MODEL FOR FUTURE TRENDS AND DIRECTIONS IN HEALTHCARE NLP USING RANKING OF TETRADECAGONAL FUZZY NUMBERS	158
<i>A. Britto Manoj and P. M. Benson Mansingh</i>	
INTRODUCTION	159
Methodology	160
<i>Tetradecagonal Fuzzy Number (a 14-sided fuzzy number)</i>	160
<i>Tetradecagonal Fuzzy Number of Ranking</i>	161
<i>Application and Results</i>	162
CONCLUSION	166
REFERENCES	167

CHAPTER 10 INNOVATIVE APPROACHES IN DRUG DISCOVERY: TARGET IDENTIFICATION, COMPUTATIONAL STRATEGIES, AND EMERGING TRENDS IN ML AND AI INTEGRATION	169
<i>Sneha Subramaniyan, Karthika Alagesan, Raji Rajmichael, Veerapandiyan Malaisamy and Jeyaraman Jeyakanthan</i>	
INTRODUCTION	170
DRUG DISCOVERY PIPELINE AND COMPUTATIONAL INTEGRATION	171
Target Identification for Drug Development	173
Role of Genomics and Proteomics in Target Identification	173
<i>Genomic Approaches</i>	173
<i>Genome-Wide Association Studies (GWAS)</i>	173
<i>Functional Genomics</i>	174
<i>Proteomic Approach</i>	174
<i>Protein Expression Profiling</i>	174
<i>Protein-Protein Interaction (PPIs)</i>	175
<i>Assay in High Throughput Screening (HTS) for Target Identification</i>	175
TRADITIONAL DRUG DISCOVERY	176
Structure-Based Drug Design (SBDD)	176
Structure-Based Virtual Screening (SBVS)	176
<i>Molecular Docking</i>	177
<i>Molecular Dynamics (MD) Simulations</i>	177
Ligand-Based Drug Design (LBDD)	178
<i>Ligand-Based Virtual Screening (LBVS)</i>	178
<i>Quantitative Structure-Activity Relationship (QSAR)</i>	178
<i>Pharmacophore Modeling</i>	179
<i>Density Functional Theory (DFT)</i>	179
EMERGING TRENDS IN MACHINE LEARNING (ML) AND ARTIFICIAL INTELLIGENCE (AI) IN DRUG DISCOVERY	179
Machine Learning in Drug Discovery	180
<i>Applications of ML in Compound Screening</i>	180
<i>De Novo Drug Design</i>	180
<i>Predicting ADMET Properties</i>	180
<i>Multi-Target Drug Design and Polypharmacology</i>	180
Machine Learning for Protein-Ligand Binding Affinity Prediction	181
INTEGRATION OF AI/ML WITH COMPUTATIONAL DRUG DISCOVERY TOOLS	183
AI in Structure-Based Drug Design (SBDD)	183
AI-ENHANCED PREDICTIVE ANALYTICS IN DRUG DEVELOPMENT	184
CASE STUDIES OF ML AND AI IN DRUG DISCOVERY	185
TRENDS SHAPING THE FUTURE OF DRUG DISCOVERY	186
THE ROLE OF AI IN PERSONALIZED MEDICINE AND DRUG DEVELOPMENT	187
CURRENT CHALLENGES AND LIMITATIONS	188
CONCLUSION	189
CONSENT FOR PUBLICATION	189
CONFLICT OF INTEREST	189
ACKNOWLEDGEMENT	189
REFERENCES	190
CHAPTER 11 AI AND NLP IN DRUG DISCOVERY AND TARGET IDENTIFICATION: FOCUS ON COVID-19	198
<i>Guneswar Sethi and Jeong Ho Hwang</i>	
INTRODUCTION	198

AI in Drug Discovery	199
<i>AI in Drug Design</i>	200
<i>AI in Polypharmacology</i>	201
<i>AI in Chemical Synthesis</i>	201
<i>AI in Drug Screening</i>	202
NLP in Drug Discovery	202
<i>Knowledge Extraction</i>	203
<i>Target Identification</i>	203
<i>Drug Repurposing</i>	204
<i>Clinical Trial Analysis</i>	204
AI-Driven Target Identification	205
AI-based target identification typically involves:	205
<i>Genomic Data Analysis</i>	205
<i>Network Biology</i>	205
<i>Multi-omics Integration</i>	206
NLP-Driven Target Identification	206
<i>Mining Scientific Literature and Databases</i>	206
<i>Gene-Disease Association and Drug Repositioning</i>	207
<i>Knowledge Graphs and Ontology-Based Target Discovery</i>	207
<i>NER in Biomedical Texts</i>	207
Case Study: ML and NLP Applications in Drug Discovery	208
<i>COVID-19 Treatment and Vaccine Discovery Using AI</i>	208
<i>Protein-Based Drug Discovery for COVID-19</i>	208
<i>RNA-Based Therapeutics and Drug Discovery for COVID-19</i>	209
<i>Generative Approaches</i>	209
COVID-19 Treatment and Vaccine Discovery Using NLP	210
Identifying Treatments for Rare Diseases Using AI and NLP	211
Predicting Drug-Target Interactions (DTIs) Using AI and NLP-Enhanced Models	211
Challenges and Limitations of AI and NLP in Drug Discovery	212
<i>Data Quality and Availability</i>	212
<i>Domain-Specific Challenges</i>	212
<i>Regulatory and Ethical Issues</i>	213
CONCLUSION AND FUTURE PROSPECTS	214
REFERENCES	215
CHAPTER 12 AI-ASSISTED PUBLIC HEALTH SURVEILLANCE OF GUT MICROBIOME	
HEALTH	220
<i>Arockiyajainmary Michealsamy</i>	
INTRODUCTION	220
GUT MICROBIOME-RELATED DISEASE SURVEILLANCE USING AI	221
Early Detection and Prediction	225
<i>Real-Time Monitoring</i>	225
RESOURCE ALLOCATION	226
Predictive Analytics	226
COMBATING BIAS IN INTEGRATING THE DATA VIA IMPROVED NLP	
ALGORITHMS	227
CONCLUSION	228
LIST OF ABBREVIATIONS	228
CONFLICT OF INTEREST	229
ACKNOWLEDGEMENT	229
REFERENCES	229

CHAPTER 13 ADVANCEMENTS IN TRANSFORMER-BASED MODELS FOR NLP IN HEALTHCARE	236
<i>Juhi Sharma, Uzma Patel, Divyanshi Salundiya, Avantika Sharma, Kratika Pathak and Sumit Govil</i>	
INTRODUCTION	237
Uses of Transformer Models in Healthcare	238
POTENTIAL CHALLENGES	239
DATA CHALLENGES IN HEALTH INDICATORS	239
LIMITATION AND FUTURE WORK	240
• Quantity and Quality of Data	240
• Computational Resources	240
• Verifying Information	240
• Handling Inaccuracies or Hallucinations	241
• Data Privacy Challenges	241
• Human Aspects	241
PRE-TRAINED TRANSFORMER MODELS	241
Transformer-Based Bidirectional Encoder Representations (BERT)	241
<i>Overview of Transformer Models: BERT, T5, and GPT</i>	241
IMPLICATION FOR HEALTHCARE	242
COMPARATIVE STUDY OF TRANSFORMER MODELS IN TRANSLATION TECHNOLOGY	243
BERT, GPT, and T5 in Translation Technology	243
Relevance of Transformer Models	244
Research Implications	244
COLLECTING AND ANALYZING SOCIAL DETERMINANTS OF HEALTH (SDOH) DATA	245
Hybrid Approaches to Relation Extraction	245
Indirect Sources of Health Information	246
<i>Census Data</i>	246
<i>Civil Registration System</i>	246
Advancing Ubiquitous Healthcare: ALPH for Streamlined Applications and Transformer Models for Clinical Insights	246
<i>Ubiquitous Healthcare</i>	246
<i>Transformer Models in Healthcare</i>	247
<i>Patient Education and Health Management</i>	247
Public Health Monitoring with Transformer Models	247
<i>Document and Topic Classification</i>	247
<i>Named Entity Recognition and Linking</i>	247
Performance Metrics and Evaluation	248
<i>Key Metrics</i>	248
<i>ROC-AUC Analysis</i>	248
Benchmark Datasets and Evaluation Standards for Healthcare NLP	248
<i>Benchmark Datasets</i>	248
<i>Evaluation Standards</i>	249
Ethical and Privacy Considerations	249
<i>Addressing Biases in Transformer Models</i>	249
<i>Regulatory Considerations</i>	249
CHALLENGES AND LIMITATIONS	250
Scalability Issues and Computational Resources	250
• <i>Varying Request and Resource Heterogeneity</i>	250

• <i>Workload Diversity and Resource Sharing</i>	250
• <i>Increasing Request and Cluster Scale</i>	251
INTEGRATING MODELS INTO CINICAL WORKFLOWS	251
FUTURE DIRECTIONS	251
Transforming Healthcare Operations: Leveraging AI for Clinical Coding, Workflow Optimization, and Patient Empowerment	252
CONCLUSION	252
REFERENCES	252
CHAPTER 14 REVOLUTIONIZING MENTAL HEALTH CARE WITH AI-DRIVEN NLP CHATBOTS: INNOVATIONS, APPLICATIONS, AND FUTURE DIRECTIONS	257
<i>Maharaja Muthuvairam Subbulakshmi, Manikandan Jayaraman, Pradeep Kumar Sriram and Jeyaraman Jeyakanthan</i>	
INTRODUCTION	258
ARCHITECTURAL FRAMEWORK OF NLP MEDICAL CHATBOTS	259
NLP MEDICAL CHATBOTS IN MENTAL HEALTH DISORDERS	260
TECHNICAL STANDPOINTS OF MEDICAL CHATBOTS IN MENTAL HEALTHCARE INTERVENTIONS	261
REAL-TIME AI-POWERED MEDICAL CHATBOTS IN MENTAL HEALTH CARE	263
TRANSFORMATIVE BENEFITS OF NLP MEDICAL CHATBOTS IN MENTAL HEALTHCARE INTERVENTIONS	263
LIMITATIONS OF NLP CHATBOTS IN MENTAL HEALTH CARE	264
CHALLENGES OF AI AND NLP IN MENTAL HEALTH CARE	265
THE FUTURE OF NLP MEDICAL CHATBOTS IN MENTAL HEALTHCARE: OPPORTUNITIES AND INNOVATIONS	265
CONCLUSION	266
CONSENT FOR PUBLICATION	266
CONFLICT OF INTEREST	266
ACKNOWLEDGEMENT	266
REFERENCES	267
CHAPTER 15 EMERGING TECHNOLOGIES IN NLP FOR HEALTHCARE	269
<i>R. Sofia and S. Yazhinian</i>	
INTRODUCTION	269
Historical Context: The Evolution of NLP in Healthcare	271
Significance in Modern Healthcare: Technical Implementation and Architecture	273
CORE NLP CONCEPTS IN MEDICAL CONTEXT	276
Text Preprocessing and Normalization in Medical Documents	276
<i>Medical Entity Recognition</i>	277
<i>Relation Extraction in Clinical Text</i>	277
<i>Semantic Analysis in Healthcare</i>	277
<i>Medical Document Classification</i>	278
<i>Medical Information Extraction</i>	278
UNIQUE CHALLENGES IN MEDICAL TEXT PROCESSING	279
Domain-Specific Terminology	279
Abbreviations and Acronyms	279
Context-Dependent Interpretation	280
Multiple Languages and Writing Styles	280
Integration with Existing Medical Systems	281
CURRENT STATE OF NLP TECHNOLOGIES IN HEALTHCARE	281
Clinical Documentation	281
Electronic Health Records (EHR)	282

Clinical Research Support	283
EMERGING NLP APPLICATIONS IN CLINICAL SETTINGS	284
Clinical Decision Support Systems	284
Patient Engagement and Communication	284
Medical Image Analysis Integration	285
ADVANCED LANGUAGE MODELS IN HEALTHCARE	286
Transformer-Based Models	286
Few-Shot and Zero-Shot Learning	287
Multilingual Medical NLP	288
CHALLENGES AND ETHICAL CONSIDERATIONS	288
Technical Challenges	289
PRIVACY AND SECURITY	289
Ethical Considerations	290
FUTURE DIRECTIONS	291
Emerging Technologies	291
Integration with Other Technologies	292
Research Priorities	292
CONCLUSION	293
REFERENCES	293
CHAPTER 16 NAVIGATING THE FUTURE OF HEALTHCARE: EXPLORING THE NEXT PHASE IN NLP	296
<i>M. K. Bhanuja and K. Suresh Joseph</i>	
INTRODUCTION	296
Relevance of NLP in Healthcare	297
<i>Clinical Documentation and Physician Burnout Reduction</i>	297
<i>Enhanced Clinical Decision Support (CDS)</i>	298
<i>Improved Patient Outcomes and Experience</i>	298
<i>Public Health Surveillance</i>	298
<i>Automation of Administrative Workflows</i>	298
<i>Sentiment and Emotion Analysis in Mental Health</i>	299
Current Landscape of NLP in Healthcare	299
Key Applications of NLP in Healthcare Today	300
Future Trends in NLP for Healthcare	305
Challenges in Implementing NLP in Healthcare	307
The Role of NLP in Shaping Personalized Medicine	309
The Road Ahead for NLP in Healthcare	311
CONCLUSION	312
REFERENCES	313
SUBJECT INDEX	317

FOREWORD

In today's rapidly evolving healthcare technology landscape, the intersection of Artificial Intelligence (AI) and Natural Language Processing (NLP) stands as a beacon of innovation and transformation. As an NLP researcher, I found this book as a comprehensive guide to navigating the complexities and opportunities presented by connecting the power of AI-driven NLP in healthcare informatics. From its foundational principles to cutting-edge applications, this book offers invaluable insights into how NLP techniques can be leveraged to unlock the potential of unstructured clinical text data, driving improvements in patient care, clinical decision-making, and biomedical research. The authors have meticulously explored both the theoretical foundations and the practical implications of these technologies, providing valuable insights for researchers, clinicians, and anyone interested in the future of healthcare. This collection is a vital resource for navigating the complex and rapidly evolving world of AI and NLP in healthcare.

As we embark on this journey through the pages of this book, we are reminded of the immense potential of AI and NLP to revolutionize the healthcare industry. Through insightful discussions, case studies, and future projections, this book serves as a resource for healthcare professionals, researchers, and stakeholders to embrace and harness the transformative power of AI-driven NLP.

This collection of chapters delves into the cutting-edge developments, challenges, and future directions of this dynamic field. From drug discovery to mental health care, and from rare disease prediction to public health surveillance, the authors explore various applications poised to revolutionize how we understand, diagnose, and treat illnesses.

I commend the editors for their dedication and expertise in compiling this comprehensive resource. I am confident that it will inspire and empower readers to embark on their own journey toward leveraging AI and NLP for the betterment of healthcare worldwide.

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PREFACE

Integrating healthcare and Artificial Intelligence (AI), particularly Natural Language Processing (NLP), holds great potential to significantly transform clinical practice, data-driven research, disease diagnosis, and drug discovery workflows. Healthcare is inherently information-rich, yet much of this information resides in unstructured formats: clinical notes, Electronic Health Records (EHRs), research publications, and patient feedback. Bridging the gap between this unstructured data and actionable knowledge is achieved through NLP. By enabling computers to understand, interpret, and generate human language, NLP empowers us to unlock patterns, trends, and crucial information that would otherwise remain hidden. In this book, we explore the fascinating realm of AI and NLP within the healthcare context. Our aim is to provide readers with a broad understanding of the principles, methodologies, and applications of AI-enhanced NLP in healthcare. From core concepts to advanced techniques and real-world case studies, this book is designed to equip healthcare professionals and researchers with the knowledge and insights needed to leverage NLP technologies for improving patient outcomes, clinical decision-making, and biomedical research.

As we begin our exploration of AI and NLP in healthcare, it is imperative to acknowledge the promise these technologies hold in revolutionizing the delivery of patient care and advancing medical research. Through synthesizing theoretical knowledge and practical visions, this book is intended for a diverse audience, including researchers, clinicians, data scientists, healthcare professionals, and students. Each chapter, spanning from initial conceptualization to practical implementation, provides readers with a deep dive into NLP's methodologies, challenges, data handling, its role in disease prediction, chatbots, and future trends within NLP-associated healthcare informatics. This book, "Natural Language Processing in Healthcare Informatics: Challenges and Future Directions," investigates this interdisciplinary discipline, exploring the intricate ways NLP is applied to extract meaningful insights from the vast sea of healthcare data.

We hope it is a valuable resource for understanding the NLP's ability to reshape and inspire further innovation in this critical field. The editors thank all contributing authors and supporting institutions that enabled the completion of this volume.

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CHAPTER 1

Introduction to Artificial Intelligence and Natural Language Processing in Healthcare**T. Sayamsruti Panda^{1,#}, Saranya Jayapalan^{2,#}, A. Shankar³ and Basant K. Tiwary^{2,*}**¹ BRIC- Institute of Life Sciences, Bhubaneswar, Odisha, India² Department of Bioinformatics, Pondicherry University, Puducherry, India³ Department of ECE, Manakula Vinayagar Institute of Technology, Puducherry, India

Abstract: The healthcare sector has rapidly evolved due to emerging trends. Integrating Artificial Intelligence (AI) and Natural Language Processing (NLP) within healthcare signifies a transformative shift in medical data analysis, interpretation, and utilization. The synergy of AI, with its ability to mimic human cognition and NLP, which empowers machines to comprehend and process human language, is essential to unlocking the hidden potential behind the vast amount of unstructured medical data. This chapter explores the fundamental concepts of AI and NLP and their applications in the healthcare sector. Various AI-enabled healthcare devices and their applications are described. The mechanism and applications of recently developed AI-powered wearable devices are also discussed. The ethical considerations of AI and NLP, as well as potential and future directions in revolutionizing healthcare delivery, are explained by examining current challenges, such as data privacy and domain-specific models. Also, this chapter describes the applications of AI and NLP in medical imaging as diverse and impactful, spanning early disease detection, workflow optimization, personalized medicine, and remote diagnostics. By automating complex processes and providing actionable insights, AI revolutionizes how medical images are analyzed and utilized. As advancements in AI continue, its potential to improve patient care, enhance diagnostic accuracy, and democratize healthcare access will only grow, making it an indispensable tool in modern medicine.

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Healthcare, AI-powered wearables, AI-enabled healthcare devices, EHR.

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INTRODUCTION

In today's world, technological advancements have become intensely woven into human life. New technological inventions have revolutionized human lifestyles through diverse applications. Artificial Intelligence (AI) has significantly transformed and simplified the challenges and obstacles associated with various day-to-day activities. It is undergoing rapid and significant growth across all domains, particularly within the medical and healthcare sectors [1, 2].

AI is the branch of computer science that creates decision-making entities, which are systems proficient in independently perceiving their environment, learning, reasoning, and taking actions to achieve desired outcomes. These actions may include problem-solving, object and word recognition, understanding and responding to natural language, making predictions, and making decisions in complex conditions [3, 4]. However, the roots of AI are deeply intertwined with various disciplines, including biology, mathematics, psychology, linguistics, and statistics. This interdisciplinary foundation is evident in the contributions of pioneers like Charles Babbage, Claude Shannon, Alan Turing, Richard Bellman, and Marvin Minsky, whose visionary work across these fields laid the foundation for countless essential AI concepts. Furthermore, significant advancements in computing, such as breakthroughs in hardware processing power and storage capacity, have provided the critical technological infrastructure that has fueled the rapid growth of AI in recent decades.

AI empowers machines to mimic human intelligence. It achieves different tasks through various Machine Learning (ML) algorithms, which are used to train them on relevant datasets to perform. Deep Learning (DL), a subfield of ML, has fueled numerous remarkable advancements, including self-driving cars. DL algorithms draw inspiration from the structure of the human brain. Natural Language Processing (NLP), another subfield of AI, utilizes ML algorithms to enable computers to comprehend and interact with human language. Fig. (1) depicts the schematic representation of AI and its subfields.

The advent of AI has impacted healthcare systems regarding disease diagnosis, treatment, and patient monitoring processes. AI technology is refining healthcare research and enhancing patient outcomes through greater diagnostic accuracy and personalized treatments. AI in healthcare excels at analyzing massive volumes of clinical data, enabling medical professionals to uncover hidden disease markers and identify novel disease associations that are difficult to detect through established conventional methods. The fusion of AI and healthcare offers immense potential for innovation and transformation while raising critical ethical concerns [5]. The continuous evolution of AI technologies drives significant

transformations across the healthcare spectrum, impacting everything from diagnostic accuracy and treatment planning to developing novel therapies and future medicine.

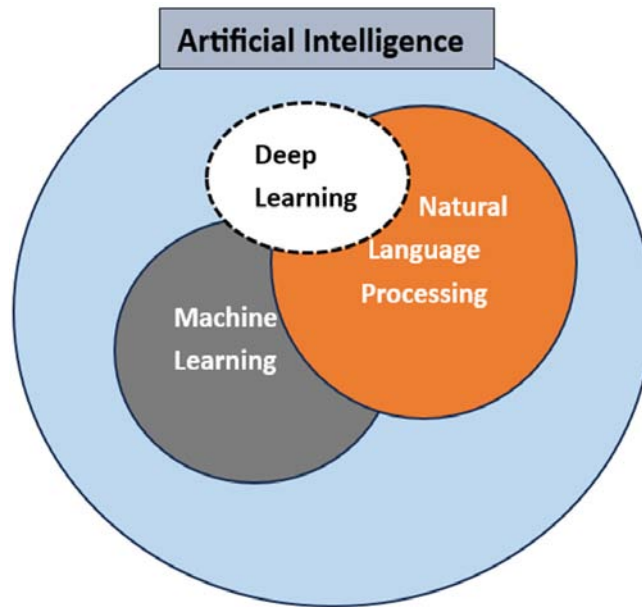


Fig. (1). Schematic representation of AI and its subfields.

Precision medicine, a keystone and one of the significant milestones of AI in healthcare, leverages ML algorithms trained on extensive and diverse datasets [6]. These datasets encompass a wide range of data formats, including biological information, medical images, and patient records, enabling the development of patient-specific therapies. Integrating AI into healthcare is advantageous in reducing the time taken for the treatment process in terms of diagnosis, timely care of the patient, and efficiency. By analyzing patient data with machine learning algorithms, healthcare providers can identify even subtle changes in patterns that may indicate an increased risk of adverse health outcomes [7].

A recent revolution in AI is the development of the AlphaFold2 [8] and AlphaFold3 [9] systems. AlphaFold3 expands upon the competencies of its predecessor, AlphaFold2, which predicts the structures of more diverse molecular assemblies. While AlphaFold2 primarily focuses on proteins and protein-protein complexes, AlphaFold3 can generate predictions encompassing proteins, DNA, RNA, ions, ligands, and chemical modifications. These enhanced models also demonstrate improved accuracy in predicting protein complex structures.

Challenges in Natural Language Processing for Healthcare Informatics

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Abstract: This chapter addresses the challenge of adapting clinical Natural Language Processing (NLP) systems for diverse healthcare environments. We adapted an existing NLP system to evaluate colonoscopy quality using pathology and colonoscopy reports from four distinct clinical settings varying in geography, practice type, pay scale, and Electronic Health Record (EHR) systems between 2013 and 2015. Adaptation revealed significant obstacles, including heterogeneous report formats, specialized clinical language, and site-specific variability, which extended development time beyond initial expectations. Effective strategies involved leveraging local EHR expertise, setting realistic deadlines, and refining the iterative system. Our findings emphasize that adapting NLP tools to new clinical contexts remains a critical barrier to widespread adoption and highlight the need for research focused on simplifying this process.

Keywords: Multimodal generative AI, Natural Language Processing (NLP), Healthcare informatics, Transformer models, Named Entity Recognition (NER), Clinical Decision Support (CDS), Electronic Health Records (EHRs), Text classification, Sentiment analysis, Text generation.

INTRODUCTION

A branch of computational linguistics and Artificial Intelligence (AI) called Natural Language Processing (NLP) studies how computers and human languages interact. It entails the application of models and algorithms to provide machines the ability to meaningfully comprehend, interpret, produce, and react to human language. Massive volumes of natural language data can be processed and analyzed using NLP, combining computer science and linguistics methods. NLP

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improves many aspects of patient care, medical research, and administrative duties in the healthcare industry. NLP is used extensively in clinical documentation and data management, automating the transcription and organization of clinical notes, reducing workloads for medical staff, and enhancing the effectiveness of documentation. NLP also makes it easier to extract data from unstructured clinical documents, such as medical reports and Electronic Health Records (EHRs), which improves data management and retrieval. NLP systems are used in clinical decision support to evaluate enormous volumes of patient data and medical literature to give doctors pertinent information and recommendations based on solid evidence, assisting them in making well-informed decisions. NLP improves healthcare by using predictive analytics to analyze patient records for early diagnosis and individualized treatment strategies. Additionally, it enhances patient engagement *via* chatbots and virtual assistants, which increases patient satisfaction by offering information, resolving queries, and setting up appointments. By evaluating patient feedback and condensing medical research, NLP improves patient care even more, keeping researchers informed and expanding medical knowledge. Furthermore, by guaranteeing conformity to legal requirements, lowering risks, and spotting irregularities in patient data to advance safety and proactive risk management, NLP helps with compliance and risk management. By automating the extraction and structuring of data from unstructured sources like clinical notes and EHRs, NLP integration into healthcare systems greatly improves data management by increasing data accessibility and usability. The analysis of patient data and a wealth of medical literature facilitates better clinical decision-making by offering insightful analysis and suggestions based on solid evidence. By automating data input and documentation procedures, NLP also increases efficiency by lowering administrative responsibilities and freeing healthcare personnel to focus on patient care. Chatbots and virtual assistants with NLP capabilities coordinate appointments, provide information, and answer inquiries, improving patient engagement and increasing treatment plan adherence. NLP also advances research by analyzing large amounts of medical data to detect trends and insights, providing researchers with the most recent findings. Lastly, by guaranteeing regulatory compliance and identifying possible hazards and abnormalities in patient data, NLP supports proactive risk management and compliance while improving patient safety.

A large-scale, cross-sectional, machine-learning-based learning analytics method was applied to conduct a comparative study on neoadjuvant versus adjuvant immunotherapy for perioperative cancer patients. Through data-driven insights obtained *via* informatics analysis, knowledge was improved, treatments were optimized, and innovation was spurred within the medical industry.

Advanced informatics and machine-learning technologies were utilized to harness large-scale global clinical and research datasets, allowing for the extraction and synthesis of high-dimensional information. Neoadjuvant and adjuvant immunotherapy were analyzed in perioperative cancer patient cohorts, and foundational metrological parameters, inherent interrelationships, and temporal evolution across various immunotherapeutic modalities were identified. Key research indicators—such as treatment timing, immune response markers,

survival outcomes, and biomarker dynamics—were systematically identified to inform a comparative framework. A data-driven scaffold was established to optimize therapeutic strategies and direct subsequent preclinical and clinical investigations by elucidating parallels and discrepancies among immunotherapy approaches. A large-sample, informatics-driven approach was employed, providing a robust foundation for the refinement of perioperative immunotherapy. Evidence-based optimization of treatment regimens was enabled, and future lines of inquiry in immuno-oncology were forecast [1].

Furthermore, a comprehensive informatics analysis was conducted to map the full scope of Liquid–Liquid Phase Separation (LLPS) research in the context of cancer. This study employed techniques such as hierarchical clustering, regression statistics, hotspot burst analysis, and the Walktrap algorithm to mine a decade of global scientific literature on LLPS in cancer. Informatics analysis in this context is as follows:

- Extracts and organizes unstructured scientific data to reveal research hotspots and development trends.
- Uses machine learning to classify research into dominant clusters and identify emerging areas.
- Highlights key molecular targets and under-explored but promising research directions.
- Maps global collaboration patterns and growth rates in this emerging field. This comprehensive informatics investigation provides a valuable reference for guiding future basic and clinical cancer research by uncovering latent knowledge and predicting promising avenues for exploration.
- Highlights how medical informatics analysis helps turn extensive, complicated biological data into information that can be put to use. Researchers may systematically map research landscapes, find necessary molecular and clinical fingerprints, and predict new trends by using data mining, machine learning, and network analysis methods on clinical and scientific information. This facilitates better decision-making while developing cancer treatments and setting priorities for research [2].

In this context, applying NLP and machine learning in medical informatics must be tailored to handle the unique linguistic complexity, unstructured formats, and privacy constraints. However, the following hypotheses and research questions are subsequently formulated.

How is the comparison of adjuvant and neoadjuvant immunotherapies enhanced by machine learning?

Deep Learning Techniques for Medical Text Analysis

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Abstract: Medical text analysis is critical to healthcare delivery because it allows for extracting important data from electronic health records, clinical notes, and medical literature. Traditional NLP techniques are frequently limited by the complexity and volume of medical language. Because deep learning techniques offer sophisticated methods that outperform conventional approaches, they have revolutionized this field. Models such as convolutional neural networks and recurrent neural networks play a key role. These models' capacity to concentrate on pertinent text is further improved by attention mechanisms. This paper examines these methods, emphasizing their uses and advantages for enhancing patient care and furthering medical research. Along with these issues, the chapter also discusses the difficulties specific to medical text analysis, including protecting patient privacy, enhancing model interpretability, and utilizing domain expertise. By looking at these areas, we show how important deep learning is for advancing medical text analysis and overcoming conventional constraints.

Keywords: Deep learning, Electronic health records, Healthcare informatics, Medical text analysis, Natural language processing.

INTRODUCTION

The healthcare industry has recently experienced an explosion of data in the form of electronic health records, clinical notes, and medical publications. EHRs may contain structured data, such as diagnoses, lab reports, *etc.* While clinical notes are essentially unstructured, text-based documents created by physicians, they contain narrative text, which introduces challenges mainly because of variations in medical terminology and abbreviations and the lack of semantic meaning [1]. The complexity of medical language makes expressions more challenging as they use many abbreviations with different definitions for the same abbreviation. Traditional methods, such as rule-based NLP, struggle with these challenges and produce inefficiencies while extracting valuable insights from that data [1, 2].

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Deep learning techniques have emerged as a more advanced solution, capable of identifying complex patterns and understanding context more effectively than traditional models, which often struggle with these limitations. This would enhance accuracy in interpreting medical text and thus support clinical decisions, research, and health management [3]. Recent DL research has dramatically transformed NLP, opening up possibilities to analyze large-scale unstructured text more effectively. Approaches like CNNs, RNNs, and transformer-based models such as BERT have shown exceptional effectiveness in medical text analysis, enhancing accuracy and processing efficiency. In this chapter, we review these DL methods and their applications in medical text analysis with experimental validation of their effectiveness.

Background

Natural Language Processing in Healthcare

Natural language processing has become an essential tool in healthcare, addressing the challenges associated with unstructured medical data and improving data analysis and interpretation. By enabling computers to comprehend and interpret human language, NLP bridges the gap between traditional data analysis methods and the vast, unstructured information in patient records, clinical notes, and research articles. Applications of NLP in healthcare are far-reaching. It can automate administrative tasks like coding and abstracting medical records, reducing the burden on healthcare providers and improving documentation accuracy [4]. Additionally, NLP aids in clinical decision-making by analyzing patient data to identify patterns, predict outcomes, and inform diagnosis and treatment. Furthermore, NLP enhances biomedical research by retrieving valuable insights from medical literature, discovering new drug targets, and deepening the understanding of disease mechanisms. The healthcare industry has traditionally relied on statistical machine-learning techniques and rule-based systems for NLP applications [3]. However, these approaches face challenges due to the ambiguity, specialized terminology, and context-dependence of medical language. The complexity and nuances of medical language often hinder the accuracy of traditional NLP systems.

Deep Learning Approaches

Deep learning, a subset of machine learning that utilizes artificial neural networks, has contributed significantly to advancements in artificial intelligence, particularly in NLP. Unlike traditional techniques that require manual feature extraction, deep learning models can automatically identify and learn intricate data patterns. Initially, neural networks such as “RNNs,” “LSTMs,” and “CNNs” were implemented for medical text analysis, providing a foundation for more advanced

deep learning models [5]. However, transformer models like BERT have revolutionized the field by delivering contextualized word embeddings that understand the meaning and structure of medical language. BioBERT and ClinicalBERT are BERT-based models. They are particularly successful in specific medical terminology because they are pre-trained in biomedical and clinical texts. These models excel in tasks such as “entity recognition,” “text classification,” and “relation extraction” by undergoing “fine-tuning” for specific applications [6].

Deep Learning Techniques for Medical Text Analysis

Fig. (1) provides a comprehensive overview of the deep learning architectures used in medical text analysis. It highlights key components such as CNNs, RNNs/LSTMs, and transformer models. The figure illustrates the workflow from input text to various tasks, including classification, named entity recognition, and relation extraction. It aligns with sections 3.1-3.3 of this paper, detailing how each architecture processes input data to perform these specific tasks.

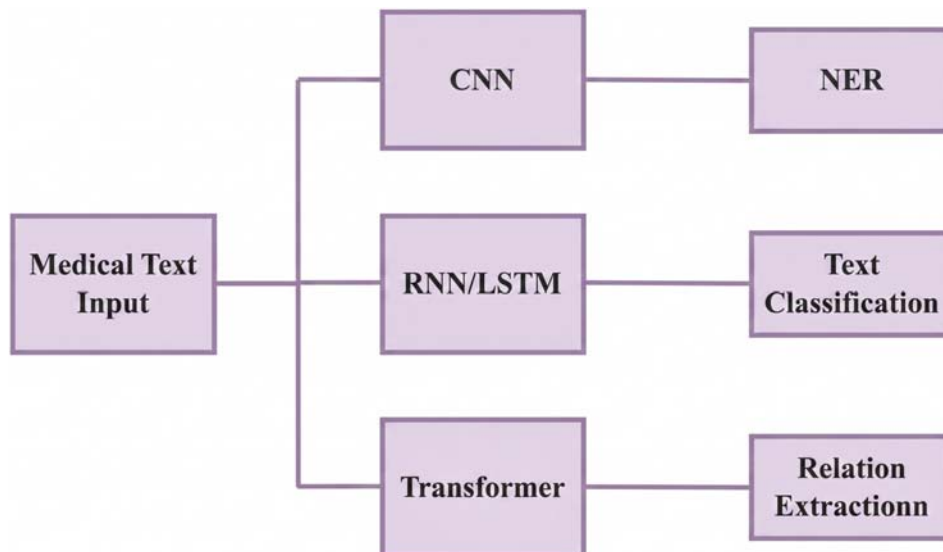


Fig. (1). Deep learning architecture for medical text analysis.

Recurrent Neural Networks

RNNs are a type of neural network designed especially for sequential data, which makes them ideal for text mining and other applications. In the context of the medical field, RNNs have been used for various applications such as named entity recognition (determining named entities like diseases or medications from text), relation extraction (defining the relationship between entities), and clinical event

Data Preprocessing and Annotation for NLP in Healthcare

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Abstract: This chapter delves into the essential processes for effectively applying Natural Language Processing (NLP) in the biomedical sector. It comprehensively covers the theoretical frameworks, practical methodologies, and specific techniques required for preparing biomedical texts for analysis. This chapter stresses the importance of carefully preparing and correctly labeling data to make NLP applications more accurate and valuable, aiming to improve patient outcomes and progress medical research. It emphasizes the role of domain expertise in the annotation process and the development of guidelines to ensure consistency and accuracy. Real-world case studies illustrate practical applications, showcasing how well-prepared and annotated datasets can improve clinical decision support systems, drug discovery, and genomics research. This chapter gives researchers and practitioners useful information about this field's theoretical foundations, current applications, and future prospects. This gives them the knowledge and tools to create advanced NLP applications that can change healthcare delivery. It also discusses emerging technologies such as deep learning and transfer learning, and highlights the importance of interdisciplinary collaboration to overcome current challenges and drive innovation in biomedical NLP.

Keywords: Annotation, Data preprocessing, Natural language processing, Tokenization, Vectorization.

INTRODUCTION

Before initiating Natural Language Processing (NLP), it is essential to comprehend the diverse categories of healthcare data and the methodologies used to prepare and identify them. Healthcare organizations utilize textual data for

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medical recording, professional annotations, and Electronic Health Records (EHRs). These files frequently encompass the patient's essential health and treatment documentation. Comprehending healthcare data necessitates the utilization of imaging modalities such as MRI, CT scans, X-rays, and specialized image analysis instruments. Clinical data is examined to enhance the comprehension of individual and collective health. This data encompasses patient attributes, diagnostic results, and medical backgrounds. Genomic data, including DNA sequences and gene expression patterns, elucidate the basic foundations of disease. Healthcare applications utilize audio data to swiftly convert speech into text, including medical consultations and doctor-patient discussions.

This data may originate from electronic health records, public health databases, medical research libraries, or specific medical devices such as wearable health monitors and imaging equipment. Preparing raw data for Natural Language Processing (NLP) necessitates distinct cleaning and structuring approaches for various data kinds. Comprehensive understanding of data retrieval and processing necessitates thoroughly examining research and best practices. Accounting for diverse data types and sources is essential to developing reliable healthcare NLP models.

In the modern era, the application of Natural Language Processing (NLP) in healthcare has gained significant momentum, transforming how medical data is processed and utilized. Healthcare institutions generate vast amounts of unstructured textual data daily, such as clinical notes, discharge summaries, medical records, and research reports. NLP can convert this unstructured data into structured information that can be analyzed, enabling better decision-making, improved patient care, and enhanced clinical research. However, the success of NLP models in healthcare heavily depends on two critical stages: data preprocessing and data annotation. The foundational step of data preprocessing involves cleaning, normalizing, and preparing raw data for analysis. In healthcare, this step becomes more intricate due to the sensitive nature of medical data and its inherent complexities, such as jargon, abbreviations, and diverse formats [1 - 3]. Moreover, annotation, which involves labeling data with meaningful tags, is crucial in training NLP models. For instance, we must accurately identify and annotate medical entities such as symptoms, diagnoses, and medications to ensure the reliability of these models' predictions. This chapter explores the critical components of data preprocessing and annotation in healthcare NLP, delving into the methods and techniques used to prepare healthcare data for machine learning models. We also talk about the mathematical formulas that are used in various preprocessing methods and show how important it is to use good annotations when developing healthcare apps that are accurate and reliable [4 - 6].

Importance of Data Preprocessing in Healthcare NLP

Data preprocessing is essential in NLP because healthcare data is often incomplete, inconsistent, and noisy. Healthcare systems utilize various forms of data storage, from digital formats to handwritten records, resulting in significant variability in how the data is structured. Preprocessing ensures that this raw data becomes usable for machine learning algorithms [7 - 9].

TEXT CLEANING

The first step in preprocessing involves cleaning the data. Healthcare data often contains extraneous information, such as spelling mistakes, abbreviations, and non-standardized terms. Text cleaning includes removing unnecessary characters, handling missing data, and correcting abbreviations using predefined medical dictionaries. This process is crucial because medical text often includes domain-specific terminology, which must be handled carefully to avoid losing meaningful information [10, 11].

Tokenization

Tokenization, a core step in preprocessing, breaks down the text into individual units called tokens. In healthcare, where the text often includes specialized terminology, tokenization must consider multi-word medical entities, such as “heart failure” or “acute myocardial infarction,” as single tokens to retain meaning. Mathematically, tokenization can be described as:

$$T = t_1, t_2, \dots, t_n$$

where T represents the set of tokens and t_1 is each token obtained from the raw text. Tokenization may involve whitespace splitting, regular expressions, or sentence-based segmentation [12, 13].

Lemmatization and Stemming

Lemmatization and stemming reduce words to their base or root forms, which helps standardize the data for model input. Lemmatization uses dictionaries to return the canonical form of a word, whereas stemming truncates words to their root. In healthcare, lemmatization is often preferred since it retains medical meanings that might be lost with crude truncation. For example, the lemmatization of “diagnoses” results in “diagnosis,” which is the more accurate form. Lemmatization, akin to branching, achieves its goals without adverse effects. Certain words, like “Histori,” may lack a root. Lemmatization is beneficial as it produces new terms [14 - 16].

Evaluating Large Language Models for RNA Interaction Extraction: A Comparative Study on Biomedical Research

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Abstract: RNA interactions are pivotal in a wide range of biological functions, including gene regulation, cellular differentiation, and the development of diverse pathological conditions (such as cancer, cardiovascular issues, and neurological disorders). Gaining insight into these interactions is key to unraveling disease pathways and pinpointing promising therapeutic avenues. Nevertheless, extracting such information efficiently from the extensive scholarly literature poses a considerable obstacle. In this work, we conducted an in-depth appraisal of Large Language Models (LLMs) to accurately identify RNA-related interactions in scientific texts. We evaluated the effectiveness of multiple cutting-edge systems, including GPT-4o and Gemini, in detecting these interactions. Our assessment centered on precision, recall, F1 scores, and ROC curve metrics in zero-shot settings, using two recognized datasets—miRNA–mRNA Interaction Corpus (MMIC) and lncRNA–protein interaction corpus (LPInsider). Among the tested LLMs, GPT-4o achieved the best accuracy, F-score, precision, and recall (0.63, 0.60, 0.66, and 0.55, respectively) for miRNA–mRNA interactions. Meanwhile, Gemini led the lncRNA–protein interaction analysis with top accuracy, F-Score, precision, and recall (0.69, 0.66, 0.74, and 0.59, respectively). These findings illuminate both the advantages and drawbacks of current LLMs for extracting RNA interactions, offering valuable guidance for future refinements in precision and overall performance within biomedical research.

Keywords: Biomedical text mining, Relation extraction, Large language models, RNA, Genes.

INTRODUCTION

RNA interactions are central to a wide range of biological processes, including gene regulation, cellular differentiation, and the emergence of multiple

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pathological conditions (including, but not limited to, cancer, cardiovascular complications, and neurological disorders). Understanding these interactions is crucial for advancing biomedical research and identifying potential therapeutic targets. However, extracting RNA-related interactions from the vast, ever-growing body of scientific literature presents significant challenges. Traditional methods of manually curating these interactions are time-consuming and often impractical given the sheer volume of published studies. The border area commonly referred to as Biomedical Text Mining (BTM) involves extracting information about biological entities and their relationships, including genes, proteins, diseases, drugs, cell types, miRNAs, phenotypes, and even broader concepts such as biological events and pathways, from scientific texts [1 - 5]. Various methods have been developed for these tasks, including dictionary matching, rule-based approaches, machine learning, deep learning, and transformer-based techniques [6 - 12]. Such approaches strive to improve both the accuracy and efficiency of information extraction in the biomedical domain, supporting research and clinical applications. The three major steps in BTM include information retrieval, information extraction, and knowledge discovery. Various studies have reported the discovery of new knowledge using BTM techniques [13 - 15].

Recently, the rise of Large Language Models (LLMs) has had a transformative effect on Natural Language Processing (NLP) and its applications in biomedical research [16 - 19]. LLMs, such as GPT-4 [20], LLaMA3 [21], Gemini [22], and Mixtral [23], have demonstrated considerable promise in various NLP tasks, including relation extraction. By leveraging massive amounts of training data, these models can comprehend and generate human language with notable sophistication. Their potential to automate the extraction of complex biological interactions from scientific texts has garnered significant interest among researchers.

This study focuses on the application of LLMs for the extraction of RNA-related interactions from scientific literature. RNA plays a pivotal role in numerous biological processes, and effectively identifying its interactions is essential for research in genomics, transcriptomics, and other related fields. Our work evaluates the performance of two state-of-the-art LLMs in extracting RNA interactions to assess their suitability for different biomedical research contexts. Specifically, we analyze these models' precision, recall, and F1 scores, along with ROC curves, to determine their effectiveness in handling the complexity and specificity of RNA-related terminology.

By offering a comprehensive comparative evaluation of these two robust LLMs, this study strives to enrich the broadening scholarly discourse regarding the utilization of artificial intelligence in biomedical research. The insights gained from this evaluation will offer valuable guidance to researchers seeking to leverage LLMs for relation extraction tasks, ultimately enhancing the efficiency and accuracy of RNA-focused research workflows.

MATERIALS AND METHODS

This study evaluates the effectiveness of LLMs in extracting RNA-related interactions from scientific literature. Unlike traditional approaches, this study focuses exclusively on using pre-existing relation corpora and large language models, eliminating the need for entity recognition and manual annotation processes. The primary goal is to assess the performance of several state-of-the-art LLMs, including GPT-4o and Gemini, in accurately extracting and categorizing RNA interactions from curated datasets.

The study utilized pre-existing relation extraction corpora, namely the miRNA–mRNA Interaction Corpus (MMIC) [24] and the lncRNA–protein interaction corpus (LPInsider) [25], which contain annotated RNA interactions. These corpora were selected based on their relevance to RNA-related studies and widespread use in the biomedical NLP community. The datasets included annotations of RNA interactions with other RNA entities, proteins, and genes, providing a comprehensive basis for evaluating the performance of the LLMs. Fig. (1) depicts the schematic architecture of the study pipeline, illustrating the Corpus Selection process, which involves identifying and curating relevant datasets based on predefined inclusion criteria to ensure comprehensive and high-quality source material for analysis, followed by LLM-based prediction and evaluation.

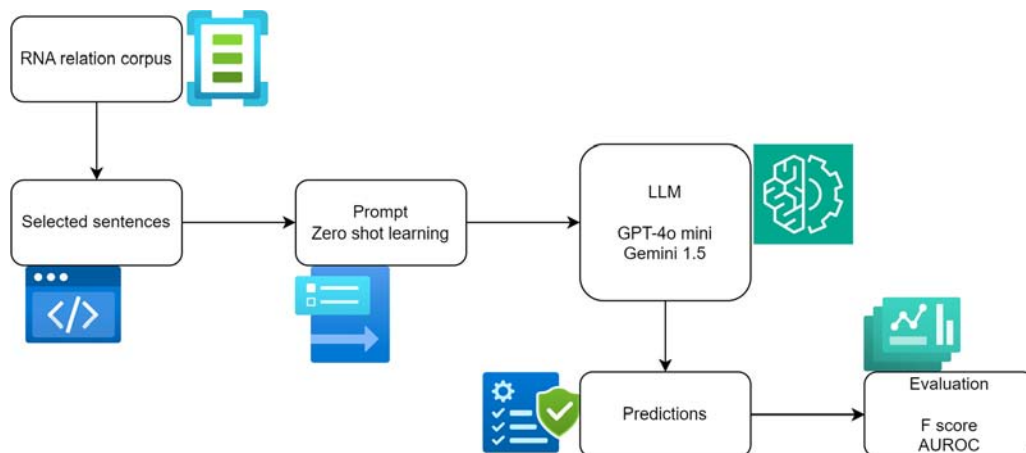


Fig. (1). Schematic architecture of the study pipeline, corpus selection.

The selected corpora were preprocessed to ensure compatibility with the input requirements of the LLMs. This preprocessing included standardization of text formats, removal of extraneous metadata, and segmentation of text into manageable units for input into the models. We selected 200 disease-specific

CHAPTER 6

Futuristic Approach for Enhancing Healthcare Using Bi-LSTM and NLP

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Abstract: Healthcare informatics transforms modern medicine using advanced computational techniques to enhance patient care and clinical decision-making. Natural Language Processing (NLP) is a key innovation in this field, which extracts critical insights from unstructured clinical data, including Electronic Health Records (EHRs), medical notes, and research articles. The vast complexity of healthcare data demands sophisticated models capable of interpreting intricate medical language. One such model, the Bidirectional Long Short-Term Memory (Bi-LSTM) algorithm, a recurrent neural network, excels in this domain. By processing sequences in both forward and backward directions, Bi-LSTM effectively captures contextual dependencies, making it invaluable for tasks such as named entity recognition, medical text classification, and sentiment analysis. By integrating Bi-LSTM with NLP, healthcare informatics can improve diagnostic accuracy, detect adverse drug reactions, and streamline clinical workflows. Bi-LSTM's ability to handle sequential data and adapt to diverse NLP tasks enables intelligent systems that support informed decision-making in healthcare. This study highlights the effectiveness of Bi-LSTM in addressing real-world challenges like early disease detection and personalized treatment planning. Experiments show that Bi-LSTM outperforms conventional LSTM models, demonstrating superior handling of long-range dependencies and higher predictive accuracy. Integrating Bi-LSTM and NLP is revolutionizing healthcare delivery, offering opportunities for personalized medicine and improved patient outcomes. Future work will focus on optimizing model performance and broadening its application across various healthcare domains, further enhancing the efficiency and precision of data-driven healthcare solutions.

Keywords: AI-driven diagnostics, Bi-directional LSTM (Bi-LSTM), Healthcare efficiency, Healthcare informatics, Natural Language Processing (NLP).

INTRODUCTION

Healthcare informatics has become a cornerstone of modern medical practice, bridging the gap between clinical needs and computational advancements to

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improve the quality, efficiency, and accessibility of patient care. As the medical field continues to generate vast amounts of data, innovative methods are required to manage, interpret, and utilize this information effectively.

Among these, Natural Language Processing (NLP) has drawn significant interest due to its ability to convert unstructured clinical data into valuable insights, including research papers, medical notes, and Electronic Health Records (EHRs). In healthcare informatics, Natural Language Processing (NLP) is an essential component that helps healthcare providers make better decisions and improve patient outcomes.

The rapid expansion of clinical data presents a unique challenge. Unlike structured data that is neatly organized in databases, clinical data is often unstructured, containing diverse information types and complex language. This complexity necessitates advanced computational models to understand the intricate terminologies and contexts unique to healthcare [1]. NLP meets these demands by allowing computers to process and analyze human language, making it possible to interpret medical records, flag potential adverse drug reactions, and assist with diagnostic support. These capabilities can provide clinicians with timely, relevant information, improving patient care in various ways [2].

The Bidirectional Long Short-Term Memory (Bi-LSTM) algorithm, a Recurrent Neural Network (RNN) designed specifically to process sequential input, is an emerging method in NLP for healthcare. Conventional LSTM networks process information in a single direction, usually from the past to the future. Despite its effectiveness, this method is limited for tasks requiring context comprehension across past and future data. By processing data forward and backward, Bi-LSTM improves this, enabling the model to identify dependencies across a sequence. In healthcare applications, where accurate analysis requires knowledge of a patient's full medical history or symptoms, this bidirectional processing is beneficial.

The Bi-LSTM architecture has demonstrated significant potential across various NLP tasks in healthcare, such as named entity recognition, medical text classification, and sentiment analysis. Named entity recognition involves identifying specific medical terms within a text, such as medications, symptoms, or diagnoses. This capability allows Bi-LSTM to automatically identify and categorize important information within patient records, aiding in developing structured databases and facilitating easier retrieval of relevant information. Medical text classification, another application, involves categorizing unstructured data into predefined categories, such as diagnoses or treatment plans. By accurately sorting information, Bi-LSTM can streamline workflows, assist in documentation, and provide healthcare providers with organized insights [3].

One specific application of Bi-LSTM in healthcare informatics is cancer prediction and diagnosis. Traditional diagnostic methods often rely on visual assessments of medical images, which can sometimes lack the precision needed for early detection of cancer cells. The Bi-LSTM algorithm offers a more nuanced approach by leveraging textual and contextual data, potentially revealing patterns or correlations that may go unnoticed through conventional analysis. By incorporating Bi-LSTM, the model can interpret the complex, nuanced language in clinical data, improving the model's ability to detect cancer cells with higher precision. For example, the model can process detailed descriptions from pathology reports or radiology notes, helping clinicians identify subtle cancer markers more accurately [4].

The bidirectional approach of Bi-LSTM also enhances the personalization of healthcare. Personalized medicine tailors treatment and care to the individual characteristics of each patient, often requiring an in-depth understanding of medical history, genetic profiles, and previous treatment responses. By processing data in both directions, Bi-LSTM can account for a patient's historical medical context and anticipate future needs, assisting clinicians in creating treatment plans that are both timely and specific to the individual. Furthermore, in pharmacovigilance, Bi-LSTM models can analyze patient records to detect potential adverse reactions, enhancing patient safety by providing early alerts to clinicians.

This study explores the integration of Bi-LSTM with NLP in healthcare informatics and underscores its transformative potential. Experimental results indicate that Bi-LSTM outperforms traditional LSTM models, particularly in handling long-range dependencies, which are common in medical data. This capability is critical in tasks such as analyzing a patient's medical history, where events are interconnected across multiple data points. The results further demonstrate Bi-LSTM's superior predictive accuracy, validating its effectiveness in real-world healthcare applications like early disease detection and personalized treatment planning [5].

As healthcare generates vast amounts of complex data, the demand for sophisticated tools like Bi-LSTM combined with NLP will only grow [6]. These tools are set to revolutionize healthcare informatics by enabling faster, more precise extraction of insights from unstructured data, improving patient care and clinical workflow. By streamlining data interpretation and enhancing diagnostic accuracy, Bi-LSTM and NLP have the potential to reshape clinical practices, making them more data-driven and patient-centered [7].

Role of Knowledge Graph in Rare Disease Prediction

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Abstract: Rare Diseases (RD), or orphan diseases, affect a small portion of the population. It is considered rare to affect less than 1 in 2,000 people. Although RDs are rare, their numbers are high: between 6,000 and 8,000 RDs are known to exist. In addition, this disease is often long and lethal. RD is characterized by phenotypic diversity that varies from one disease to another and between patients with the same disease. It became difficult to predict despite the low prediction rate and several problems, such as limited access to accurate diagnosis, a lack of knowledge about the disease, and a lack of scientific understanding of the condition. Biomedical text mining has become an essential tool in recent years to extract information from structured and unstructured text and provide valuable insights for drug discovery, disease prediction, and disease-disease interaction prediction. This chapter introduces rare diseases and the techniques and tools used to predict rare diseases.

Keywords: Biomedical text mining, Knowledge graphs, Phenotypic diversity, Rare diseases.

INTRODUCTION

Rare diseases, often known as orphan diseases, typically afflict tiny groups of people, with an estimated 1 in 2000 persons affected, in contrast to diseases like cancer and Alzheimer's [1 - 3]. As the World Health Organization (WHO) indicates, RDs are those where the number of people infected is 0.65 % to 1 % of the total population. Even though they are uncommon, some RDs have a sizable

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population afflicted by specific illnesses [4, 5]. RDs are characterized by a wide range of phenotypes that vary from one infection to the next and from one patient to another who has a similar sickness [6, 7]. *Alkaptonuria*, *Cystic fibrosis*, *Muscular dystrophy*, *Angelman syndrome*, *Haemophilia*, *Achalasia*, etc., are some of the examples of rare diseases [8].

Alkaptonuria is a rare inherited genetic disease that is brought about by a change in the HGD gene for the chemical homogentisate 1,2-dioxygenase; if an individual receives a strange duplicate from the two guardians, the body collects a moderate substance called homogentisic acid in the blood and tissues [9, 10]. *Cystic fibrosis* (otherwise called “mucoviscidosis” is liable for respiratory and gastrointestinal issues, affecting around 1 in 5,000. A group of illnesses known as *muscular dystrophy* results in progressive weakness and muscle mass loss. Children with muscular dystrophy, a primary immune deficiency, have symptoms that include aberrant gene mutations that prevent the body from producing the proteins necessary to form healthy muscle [11, 12].

Angelman syndrome is a complex hereditary problem that essentially influences the sensory system. Trademark elements of this condition include delayed development, intellectual disability, severe communication disability, and issues with motor development and coordination. Most impacted kids likewise have intermittent seizures (epilepsy) and a small head size [13, 14]. One fascinating disorder that affects the blood's ability to clot is *hemophilia*. Males are affected by the vast majority of *hemophilia* [15, 16]. *Achalasia* is a swallowing disorder that affects the esophagus, the tube that connects the mouth and stomach. When nerves are damaged, it is difficult for the throat muscles to move food and liquids into the stomach [17, 18].

Since it provides a detailed picture of infections, the data extraction regarding RD phenotypes is critical and could be used to guide clinical judgment and clinical consideration [19]. In addition, this disease is often long and lethal. The prediction rate of RDs is low [20 - 22]. A large volume of information about rare diseases is encoded in organized sources like databases and ontologies, yet in addition in composed texts, for example, research articles, clinical cases, clinical trials, drug safety reports, health agency newsletters, as well as information from social media, websites, and health forums [23, 24].

Recently, biomedical text mining has become one of the most critical areas to process and dissect enormous volumes of unstructured data accessible in any space or field of information, and it gives valuable knowledge in disease predictions, disease-disease interaction predictions, drug discovery, and so on [25 - 27]. A few shared tasks, such as BioCreative [28], i2b2 [29], BioNLP shared

tasks [30], and DDI Extraction [31], have contributed to the development of examination in NLP strategies as applied to the areas of science and biomedicine. Subsequently, numerous frameworks and instruments (MetaMap [32], cTakings [33], and MedLEE [34]) have been produced to acknowledge the substances and extract connections between these domains.

This chapter briefly introduces rare diseases and symptoms, biomedical resources, architecture, and state-of-the-art approaches to extract knowledge about RDs from biomedical literature. (Fig. 1) illustrates the architecture of the rare disease knowledge graph.



Fig. (1). The architecture of rare disease knowledge graph.

Biomedical Resources/Corpora and Databases

Selecting the appropriate corpus and biomedical resources is crucial for assessing the effectiveness of any text-based knowledge discovery process [35 - 37]. Different types of corpora and databases are available as open-source [37].

ICD: As a medical services order system, the ICD offers a set of demonstrative codes for classifying illnesses, including a broad range of symptoms, adverse effects, unexpected findings, demonstrations, social circumstances, and external causes of illness or injury [ICD07]. It is utilized for factual purposes and as a coding framework in clinical data sets [38]. The ICD's inability to resist perceiving the outcome of the treatment course is one of its limitations [KPM+08]. Similarly, the final ICD-coded finding may need several patient visits and is rarely clarified during the initial visit [39].

DO: Human Disease Ontology (DO) DO is an ontology for portraying the characterization of human diseases coordinated according to a clinical viewpoint of disease etiology and area [KAF+15]. DO was created to make a solitary structure for the arrangement of diseases to combine the portrayal of diseases into an ontology from the numerous and different existing phrasings and vocabularies [40]. The target of DO gives an unmistakable definition to every disease. It empowers the predictable use and application for explaining biomedical information and is incorporated with other phrase-based ontologies like MeSH [41], ICD [38], NCI's thesaurus [42], SNOMED [43], and OMIM [44].

Leveraging AI and ML to Enhance Focused Ultrasound Treatments for Essential Tremors

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Abstract: In today's world, technological advancements in the medical field have revolutionized healthcare, dramatically enhancing diagnosis, treatment, and patient care. For example, AI and ML algorithms can now precisely analyze and observe medical images. The quality of life of individuals with Essential Tremors (ET) is significantly affected, and Focused Ultrasound (FUS) has become a viable non-invasive therapeutic option. However, precision targeting and customized therapy regimens are necessary for maximizing FUS treatment for ET. To improve the effectiveness of FUS in ET therapy, this work investigates the integration of Artificial Intelligence (AI) and Machine Learning (ML). In order to assess patient data, enhance imaging precision, and customize therapy parameters, we implemented cutting-edge AI algorithms. According to research, utilizing AI and ML in FUS can transform ET management and provide a more efficient and personalized treatment choice. The creation of real-time AI tools and additional validation will be the main goals of future research. For instance, imaging processes can be performed using computer-assisted interpretation without human intervention and in a more accurate way. The quality of life of people affected by Essential Tremors (ET) is significantly low, and thus, Focused Ultrasound (FUS) has emerged as a promising non-invasive treatment. However, precision targeting and bespoke therapeutic approaches must be employed to bridge any resultant gaps in FUS treatment for ET. This work investigates ways in which Artificial Intelligence (AI) and Machine Learning (ML) can be employed to enhance the efficacy of FUS treatment in ET therapy.

Keywords: Artificial Intelligence (AI), Essential Tremors (ET), Focused Ultrasound (FUS), Machine Learning (ML), Precision targeting.

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INTRODUCTION

Essential tremor [1] is one of the most common movement disorders worldwide. This condition is mainly characterized by involuntary shaking of hands, head, or voice. According to an article in PubMed Central [2], the global prevalence of ET was estimated to be 0.32% (24.91 million people) in 2020. This prevalence rises with age, from 0.04% in people younger than 20 to 2.87% in those 80 or older. ET is also more prevalent in men as opposed to women, with a male prevalence of 0.36% and a female prevalence of 0.28%. Some patients derive relief from medication and lifestyle changes; however, in many cases, this fails to improve the condition, and therefore, attention has been drawn to seeking alternative treatments. On this basis, breakthroughs in Focused Ultrasound (FUS) provide promising non-invasive therapy options. Because FUS does not require surgical incisions, clinicians can target the brain areas where tremor generation occurs.

FUS works by overlaying high-frequency sound waves to create tight, focused thermal or mechanical impacts in specific brain tissues. The effectiveness of FUS therapy [3] lies in the extent to which tremors decrease, making the patient's lifestyle simpler and more comfortable. The optimality of the treatment parameters, coupled with the proper selection of patients, will determine the success of the therapy. In real-time monitoring of responses to the procedure, responses from the patient are required to make alterations for better outcomes.

The introduction of AI combined with ML [4, 5] into FUS protocols can be a transformative opportunity to enhance efficiency and efficacy in treatment. These technologies will analyze large volumes of patient data to identify those likely to benefit from FUS, considering disease severity and comorbidities. AI and ML might further help in planning treatment by predicting optimal parameters involved in ultrasound application, such as frequency and intensity, tailored to the profile of each patient.

AI-driven real-time monitoring enables online adjustment of treatment parameters during treatment, efficiently and precisely targeting areas of the brain that cause tremors. It also uses AI in post-treatment analysis to predict long-term results so that the clinician can adjust follow-up care accordingly. Integrating AI and ML can significantly enhance the approach taken to treat essential tremors with FUS, ultimately improving patient outcomes and increasing personalization of the process [6].

RELATED WORKS

In one of the earliest studies conducted by Lynn *et al.* [7] in 1942, an efficient focused ultrasound generator was developed and successfully tested, which

demonstrated the possibility of producing focal heating in paraffin blocks and the targeted destruction of fresh liver tissue with minimal surface effects. Local cerebral changes induced by high-intensity focused ultrasound were observed in animals and were evidenced by behavioral disabilities that resolved within 2 to 16 hours after exposure, despite passing through the scalp, skull, and meninges. However, previous attempts have resulted in severe injuries to the skin and subcutaneous tissues. The above article suggests ways to optimize focused ultrasound application to increase focal effects in the brain while reducing or removing surface injuries.

The study by Haar G. *et al.* [8] shows that High-Intensity Focused Ultrasound (HIFU) is quickly becoming accepted as a treatment modality, allowing non-invasive tissue heating and ablation for many applications. HIFU treatments are most commonly performed as a single session, often with the patient fully conscious, lightly sedated, or under light general anesthesia. The primary benefit of HIFU over any other thermal ablation technique is that there is no need to place probes into the target tissue. Such highly focused beams are created from sources that are either external to the body, used for the treatment of tumors in the liver, kidney, breast, uterus, pancreas, and bone, or located in the rectum, which is used for the treatment of the prostate, and intended for rapid heating of a target tissue volume with minimal effects on tissue in the ultrasound propagation path. However, because of the broad applicability of HIFU, many devices have been developed for extracorporeal, transrectal, and interstitial treatments to optimize application-specific delivery. Their principles of operation will be described, along with an overview of the physical mechanisms governing HIFU propagation and HIFU-induced heating. Current methods of characterizing HIFU fields and quantifying HIFU exposure and its associated effects are given much focus in the present article.

The paper by Bystritsky *et al.* [9] presents an approach to several neuromodulation techniques, such as DBS and VNS; there is increasing interest in these methods in clinical research. However, the currently available techniques suffer from problems associated with a lack of specificity and invasion. The present article looks into LIFUP, a noninvasive method of brain stimulation that can be delivered precisely through the skull and even integrated with another imaging technique like fMRI. LIFUP is in preclinical testing. There is, however, promise for future clinical applications in more than 50 years of focused ultrasound research on neuronal tissue.

A recent study by Gail R *et al.* [10] describes the noninvasive application of tightly focused ultrasound beams to selectively kill cells within a focal volume while sparing surrounding tissues. This makes it applicable in fields like urology,

A Mathematical Model for Future Trends and Directions in Healthcare NLP Using Ranking of Tetradecagonal Fuzzy Numbers

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Abstract: In this exploration, we adopted a ranking approach based on tetradecagonal fuzzy numbers, which are 14-sided polygons through which transit patterns such as demand, supply, and transportation value are represented. Vogel's Approximation Method (VAM), a traditional method in fuzzy studies, is used to solve fuzzy transportation problems to obtain fuzzy nominal results. Tetradecagonal fuzzy values suggest an excellent nutrient rate for a fruit diet at a low cost. The fruit diet will provide high-energy and nutritionally essential food for healthcare. This chapter indicates compelling growth in the use of fuzzy logic in healthcare NLP. The nominal result offers a constructive explanation that focuses on the data's imprecision while providing an initial solution. Our path is constructive in amending fruit diets. By assimilating tetradecagonal fuzzy numbers, which are 14-sided polygons, we can accurately model the costs and nutritional values of various fruits, ensuring that the diet remains within budget and provides high energy and essential nutrients. The ranking schema in fuzzy transportation for healthcare in NLP is adequately commensurate with cost moderation and health supplement requirements, making it feasible to map a well-balanced fruit that increases health benefits for healthcare NLP. Ranking tetradecagonal fuzzy numbers allows us to exhibit compelling upgrades in the application of fuzzy logic to transportation and dietary optimization, offering both practical and nutritional advantages.

Keywords: Fuzzy transportation problem, Fuzzy ranking approach, Healthcare data NLP, Macronutrients, Micronutrients, Nutritionally balanced diet, Tetradecagonal fuzzy number.

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INTRODUCTION

When discussing the nutrients and the strength of cuisine, it should complement the food. Most of the foods people eat depend on their interests. Gastronomy etiquette can diverge from one locality to another in society and from one home to another. Fruits are built in periodically to upgrade fitness conditions. Fruits are vital and are packed with iron, minerals, potassium, zinc, and trace metals [1] [2]. Fruits encompass an immense source of vitality that is important for our bodies. Fruits provide enough iron absorption and contain several vitamins and fibres that boost people's energy levels and help them sustain their health.

In health care, fruits are broadly excellent in the origin of macronutrients, and they also contain pectin, which contributes a considerable volume to a well-balanced diet and helps abdominal development. Everyone must take botanical fruits in their daily routine. As a result, it increases efficiency and intensity. It generates fresh vitality for all climatic conditions. The essence of a fair, well-balanced diet will be modified according to fiscal status, and the anatomical state, and fair health supplements of fruits can be appropriated into triple stipulations of massive amounts, reasonable amounts, and small amounts. Even nutritional theory constantly lifts the community's health and wealth care and pacts with fruit absorption, utilization, and management. The individual who takes fruit health supplements as part of a routine to measure their well-balanced diet will have long-term health benefits and avoid inflammation. It grants health care perquisites and protects us from sickness [3]. Blackberry, litchi, strawberry, sapota, and pomegranate are fruits regularly used by people all over the country because they are all upscale sources of macronutrients in health care supplements. It casts divergence for a well-balanced dietary element, giving macronutrients and micronutrients. Frequently passed down, Blackberries are the finest source of cellulose, and cellulose is a rich energy source for accomplishing work. Blackberries consist of manure, which is indeed a macronutrient for the body. Blackberries help us to epitome comfortably and contain a lot of vitamin C. Litchis are high in macronutrients. It aids in preventing many disorders and presents fair and fresh skin. Litchis consist of depressed calories. Litchis have inhibited oxidation, which protects health and indicates the avoidance of tumors. Health supplements make Litchi a tumor-vigilant fresh produce. Strawberries are typically termed a dietary element that contains carotene-beta and macronutrients that contain A. Strawberries contain enzymes that are very needed for digestion. Strawberries are rich in fiber, and they have developed a healthcare system. The accessible way to boost fiber absorption is to eat sapota, which is rich in health benefits and macronutrients. Sapota involves cuprum and calcium, a good source of evolving immunity within the body. Sapota guides curtail density, which will boost our metabolism. Sapota involves iron components, which are a significant

part of plasma. Pomegranate deals like a cloak of oxygen, and it battles heart inflammation. Pomegranates contain many health supplements that protect us from many syndromes, and they are a rich source of macronutrients in healthcare.

In this exploration, we spotlight fruitage, which contains a fantastic amount of macronutrients that we require daily. For our well-balanced diet, blackberries, Litchis, Strawberries, Sapota, and Pomegranates are taken appropriately. Scaling the tetra-decagonal of uncertain sets mapped by the penalty method has been exceptional in acquiring the macronutrients and micronutrients for healthy supplements. The grit of the analysis contributes to illustrating the choice for fitness by adopting a fitting dietary element that has a minimal amount.

Methodology

- A fuzzy set \tilde{C} X is characterized by a membership function. $\mu_{\tilde{C}}(x)$ Which associates each point in X with an actual number in the interval [0, 1]. The value of $\mu_{\tilde{C}}(x)$

Represents the grade of membership of $x \in \mu_{\tilde{C}}(x)$.

- The α -cut of the fuzzy set \tilde{C} The universe of discourse X is defined as

$$\tilde{C}_{\alpha} = \{x \in X / \mu_{\tilde{C}}(x) \geq \alpha, \text{ where } \alpha \in (0,1) \}.$$

- A fuzzy set \tilde{C} It is defined on the set of real numbers. R is a fuzzy number if it is a membership function. $\tilde{C}: R \rightarrow [0,1]$ has the following characteristics
 - a. \tilde{C} It is piecewise continuous.
 - b. \tilde{C} It is expected that if there is an $x \in R$ such that $\mu_{\tilde{C}}(x) = 1$

Tetradecagonal Fuzzy Number (a 14-sided fuzzy number)

An uncertain set of \tilde{C}_T is a tetradecagonal uncertain set denoted by

$$\tilde{C}_T = (c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8, c_9, c_{10}, c_{11}, c_{12}, c_{13}, c_{14})$$

and $c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8, c_9, c_{10}, c_{11}, c_{12}, c_{13}, c_{14}$ The numbers are accurate, and the group function is given below,

CHAPTER 10**Innovative Approaches in Drug Discovery: Target Identification, Computational Strategies, and Emerging Trends in ML and AI Integration****Sneha Subramaniyan¹, Karthika Alagesan¹, Raji Rajmichael¹, Veerapandiyan Malaisamy¹ and Jeyaraman Jeyakanthan^{1,*}**¹ *Department of Bioinformatics (4th Floor), Science Block, Alagappa University, Karaikudi – 630003, Tamil Nadu, India*

Abstract: In modern pharmaceutical research, drug discovery is the cornerstone that drives the development of new drugs for life-threatening diseases. A growing amount of evidence suggests the promising applications and benefits of Machine Learning (ML) and Artificial Intelligence (AI) in drug discovery. The ideal of personalized medicine in drug discovery is currently being realized through neural network approaches that tailor therapeutic strategies to patients based on their genomic profiles. Combining modern, sophisticated computational algorithms with high-throughput biomedical research is the current gold standard for drug discovery. Since AI and ML are still in their infancy, these scientific paradigms offer significant opportunities for massive technological innovations. Besides the apparent scientific benefits, the expenditure, manpower, and time required for traditional drug discovery are significantly reduced. In this chapter, we have implemented a comprehensive case study review strategy to explore and uncover the potential intricacies and probable limitations of learning algorithms in drug discovery research. The advent of bioinformatics and its subsidiary computational methodologies has revitalized crucial phases of drug discovery, such as the discovery of novel drug targets, screening, candidate molecule validation, and preclinical testing. Thus, this chapter explores the latest innovations and benefits of self-learning algorithms in pharmaceutical research and development, highlighting their potential future opportunities in drug design and drug discovery.

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Computer-aided drug design, Structure-based drug design, Ligand-based drug design, Personalized medicine.

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INTRODUCTION

The global healthcare landscape is being transformed by Artificial Intelligence (AI) and Machine Learning (ML), revolutionizing diagnostic and treatment processes. Conventional drug discovery techniques relied heavily on human expertise and manual procedures, which resulted in errors, delays, and inadequacies. This process requires extensive experiments, including *in vitro* and *in vivo*, with drug development taking 10-15 years and costing \$1-2 billion per drug. Conversely,

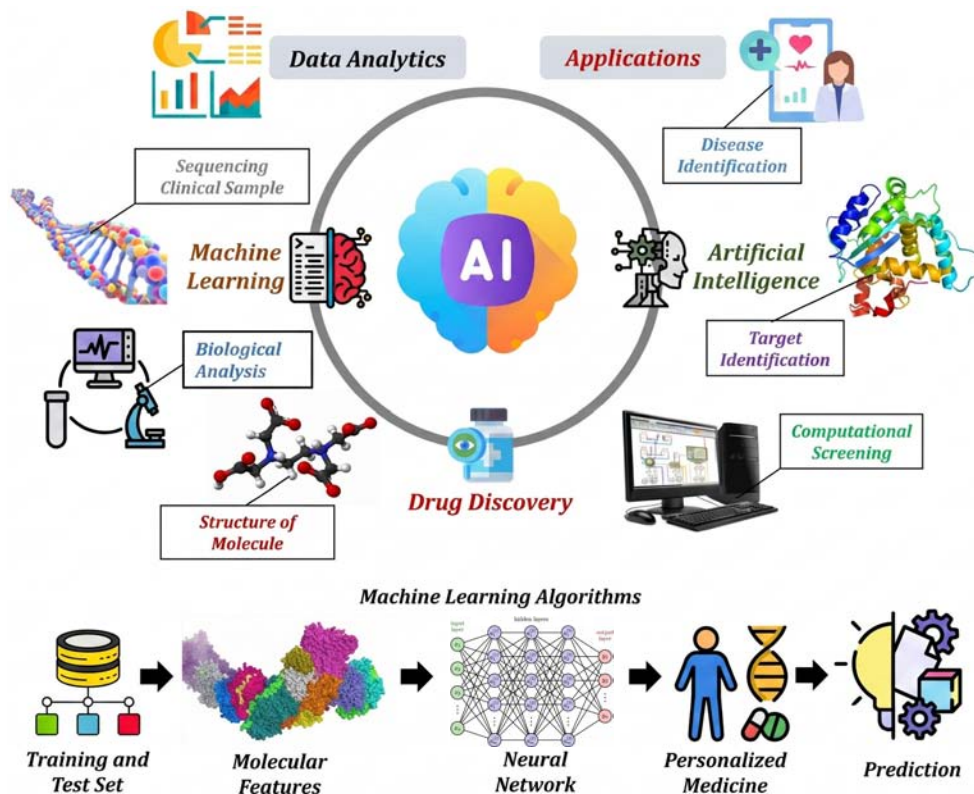


Fig. (1). Schematic representation of artificial intelligence and machine learning integrated in drug development and discovery.

Computer-Aided Drug Design (CADD) provides a more efficient alternative, substantially reducing the time and cost required to discover new therapeutic compounds [1]. In recent decades, AI has played a transformative role in drug design by streamlining precision and speed. This enhances the accuracy of drug discovery while lowering the expenses in clinical trials [2, 3]. AI is the ultimate goal, with ML acting as the brain and DL as the driving force. This system deals

with unorganized data, such as text and images. AI, ML, and DL are interconnected through a complex system, using mathematical processes and algorithms to manage data in ways that mimic the human brain. This advanced approach requires substantial computing power and data (Fig. 1).

In the realm of AI, Machine Learning (ML) is a discipline that leverages statistical techniques to learn, either with or without substantial human involvement. ML can be categorized into three types: supervised, unsupervised, and Reinforcement Learning (RL) [4]. Supervised learning utilizes input and output data to develop predictive models, applying methods such as regression and classification. The classification output determines if a molecule is biologically active, while the regression output predicts the binding affinity score. Categorizing and analyzing data without external guidance is the aim of unsupervised learning, which includes clustering and feature-finding techniques. Through unsupervised ML, disease subtypes can be clustered, and disease targets can be identified using feature-finding methods. RL is utilized to make decisions and take action in a given context.

In the present scientific landscape, the explosion of medical data has coincided with innovation in computational technologies such as cloud computing, GPUs, and TPUs, alongside the emergence of deep learning. The enormous datasets generated from molecular screening, personal health records, and public health databases can be efficiently analyzed using AI, facilitating drug discovery and diminishing failure rates [5]. AI is a revolutionary tool that bridges the knowledge gap between disease diagnosis and the identification of potential treatment agents. Its ability to analyze large datasets and perceive patterns is crucial for optimizing drug discovery processes, intensifying the accuracy of predictive models, and improving effectiveness across the drug discovery pipeline, including clinical trial management. In light of these factors, AI holds the potential to revolutionize drug discovery, providing extensive benefits to patients and the healthcare industry [6]. This chapter highlights modern strategies in drug discovery, focusing on target identification, computational methodologies, and the incorporation of ML and AI. These innovations enhance efficiency, accuracy, and prognostic capabilities, driving the development of novel therapeutics and transforming the pharmaceutical landscape.

DRUG DISCOVERY PIPELINE AND COMPUTATIONAL INTEGRATION

The pipeline of drug discovery comprises multiple stages that can be broadly categorized as follows: preclinical development, clinical trials, hit-to-lead optimization, target identification, and hit identification [7].

AI and NLP in Drug Discovery and Target Identification: Focus on COVID-19

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Abstract: The integration of Artificial Intelligence (AI) and Natural Language Processing (NLP) is evidently accelerating the processes of drug discovery and target identification. The conventional techniques employed in these domains have been characterized by high labor intensity and cost, frequently resulting in extended timelines and substantial financial outlays. AI and NLP provide innovative solutions to streamline and enhance these processes by automating and improving accuracy. AI technologies, including Machine Learning (ML) and Deep Learning (DL), facilitate predictive modeling of drug activity, design novel drug molecules, and optimize lead compounds for improved efficacy and safety. Concurrently, NLP processing techniques facilitate the extraction of actionable insights from extensive biomedical literature and databases. This enables uncovering gene-disease associations, potential drug repurposing opportunities, and relevant biomolecular interactions. The combination of AI-driven predictive analytics with NLP-extracted knowledge enables researchers to achieve more accurate identification of therapeutic targets and promising drug candidates. This integrative approach accelerates the drug development timeline and enhances the precision of target identification. Despite these advancements, challenges such as data quality, model interpretability, and the necessity for experimental validation persist. Future developments in AI and NLP promise to refine drug discovery processes, leading to more effective and targeted therapeutic interventions and ultimately improving patient outcomes.

Keywords: Artificial Intelligence (AI), Natural Language Processing (NLP), Drug discovery, Target identification, Machine Learning (ML), Deep Learning (DL).

INTRODUCTION

Drug discovery and target identification are very pivotal for the pharmaceutical industry. However, the traditional approaches are often slow, expensive, and

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incompetent. Drug discovery is a laborious process that involves identifying disease-related genes, followed by experimental validation, high-throughput screening, lead optimization, preclinical testing, and clinical trials, which can take up to 15 years and cost \$1 to \$2 billion to bring a single drug to market [1, 2]. Due to prolonged clinical trial durations, nearly 90% of drug candidates failed to advance past phase I [3]. The difficulties of bringing drug candidates from the lab to the clinic are highlighted by the substantial financial support required, which is important for pharmaceutical corporations and academic organizations. Due to its poor success rate, there is an increasing demand for cutting-edge technologies to expedite and simplify this process. Thus, to increase the success rates of lead identifications in clinical trials, researchers increasingly use large-scale computational screening and molecular docking techniques [4]. However, traditional methodologies often suffer from inefficiencies and inaccuracies in predictive outcomes. The integration of DL and ML, both subsets of AI, has emerged as a promising solution to these challenges [5]. AI tools can accurately predict complex properties and relationships within biological systems while maintaining low computational costs, leading to their adoption in the pharmaceutical landscape [6]. ML has become an integral part of modern drug discovery, leveraging various algorithms such as DL, Bayesian Networks (BN), Random Forests (RF), clustering methods, and Support Vector Machines (SVM). Each of these algorithms has specialized functions: DL models are particularly effective at handling large datasets, supporting tasks like clinical imaging [7, 8], Virtual Screening (VS) [9, 10], and predicting bioactivity [11]. Bayesian networks contribute by predicting toxicity levels and patient responses to treatments, while RF is employed to identify molecular targets and select critical features [12, 13]. Clustering methods, including k-means and hierarchical clustering, help group drugs or patients with similar molecular or clinical characteristics. Other techniques like Principal Component Analysis (PCA) further simplify complex, high-dimensional data, revealing patterns that enhance understanding of toxicity risks and pharmacokinetic properties [14]. SVMs are particularly valuable for classifying data into distinct categories, essential for accurately predicting pharmacokinetic behaviors and assessing potential toxicity [15].

The convergence of AI and ML within drug discovery has already begun to streamline the R&D pipeline, easing access, reducing costs, and improving the efficiency of drug development. By adopting these technologies, the pharmaceutical industry is poised to overcome the limitations of traditional methodologies and bring effective treatments to market more rapidly.

AI in Drug Discovery

The AI-based computational modeling approach has transformed drug discovery by improving drug identification, target discovery, and prediction of toxicity and efficacy. ML algorithms have played an important role in expediting the discovery of lead compounds from large chemical libraries, including over 106 million molecules, further effectively addressing off-target toxicity [16]. Innovative tools such as AlphaFold, developed by Google's DeepMind, have transformed protein structure prediction, a crucial aspect of drug development.

Moreover, recent advancements have enabled AI to predict novel drug candidates and discover therapeutic peptides. Platforms, such as Deep-AmPEP30 [17] and ACP-DL [18], leverage DL methodologies to identify antimicrobial and anticancer peptides. Additionally, AI technologies are increasingly utilized to optimize drug dosages; for instance, the AI-PRS platform employs neural networks to correlate drug combinations and dosages with therapeutic efficacy. Various ML and statistical techniques also forecast potential disruptions in protein-protein interactions, enhancing our understanding of drug dynamics. AI's influence extends across multiple stages of drug discovery, from lead compound identification to structure-based drug design, drug repurposing, and dosage optimization. Table 1 summarizes the key AI techniques and their roles in drug discovery.

Table 1. Roles of AI techniques in drug discovery.

AI Technique	Role in Drug Discovery	Key Application
Machine Learning (ML)	Prediction of drug-target interaction	Lead compound identification
Deep Learning (DL)	Protein-ligand docking, virtual screening	Structure-based drug design
Natural Language Processing (NLP)	Text mining from biomedical literature for target identification	Biomedical literature mining
Reinforcement Learning (RL)	Optimization of drug design and synthesis process	Drug synthesis pathways

AI in drug screening enables researchers to dramatically reduce the number of compounds that require experimental testing, saving time and resources while increasing the probability of success. Furthermore, AI-driven drug discovery encompasses four major categories: drug design, polypharmacology, chemical synthesis, and drug screening. Fig. (1) illustrates these categories, highlighting AI's distinct roles.

AI in Drug Design

AI is revolutionizing medication design by significantly speeding the identification of possible therapeutic candidates. The initial step is collecting massive amounts of genomic, proteomic, and chemical data from many sources, including experimental research and literature. This data is then utilized to train AI models, allowing ML algorithms to detect complex relationships between chemical structures and biological processes. By analyzing Structure-Activity Relationships (SAR), AI can predict how specific molecular alterations affect biological processes. Based on these findings, AI algorithms can predict new medication candidates, focusing on molecules most likely to bind successfully to certain biological targets. But AI does not stop there; it goes one step further,

AI-Assisted Public Health Surveillance of Gut Microbiome Health

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Abstract: Natural Language Processing plays a significant role in public health surveillance as it analyzes multimedia data to understand epidemics, forecast outbreaks, and address data-integration challenges. Syndromic surveillance systems that focus on symptoms rather than diagnoses provide immediate but less specific information for public health surveillance. By leveraging AI tools for surveillance, healthcare professionals can optimize interventions, identify gut microbiome modulation, and prevent chronic diseases. AI-driven approaches enable multi-omics data analysis, encompassing genomics, proteomics, and metabolomics, and provide extensive insights into the gut microbiome's influence on host metabolism and pathological conditions. Furthermore, AI can predict host phenotypes derived from gut microbiome characteristics, facilitating early identification of different disease states and improving human health outcomes. Generative AI can facilitate advanced analytics and provide new interventions for complex disease surveillance. For instance, unstructured clinical notes in medical examiners' case reports, social media activities, and news reports are potentially proper text signals currently inaccessible at the population level. This chapter highlights the diverse applications of AI in public health surveillance, emphasizing its role in optimizing decision-making, safety monitoring, and cognitive assessments across different contexts. We emphasize that the collaboration between AI and gut microbiome research has the potential to transform public health monitoring, personalized nutrition, and global metabolic health.

Keywords: AI-driven public health surveillance, Gut microbiome health, Local detection, Global epidemic monitoring, Early warning.

INTRODUCTION

Research on the human gut microbiome has evolved due to the rapid development of Artificial Intelligence (AI) techniques, particularly Machine Learning (ML) and Deep Learning (DL) [1]. AI possesses significant applications in advanced public health surveillance by enhancing data collection, analysis, and epidemic prediction capabilities [2]. Incorporating artificial intelligence into various

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information sources, including social networks, mobile health data, and digital health records, has revolutionized traditional surveillance systems by providing proactive interventions and real-time monitoring [3, 4]. However, in health surveillance, the widespread use of AI commenced recently with the onset of COVID-19. Gut microbiota is linked to several chronic diseases [5, 6], including Inflammatory Bowel Disease (IBD), diabetes, liver disease, chronic heart disease [7 - 9], cancers, HIV, and autism [10, 11]. By leveraging Natural Language Processing (NLP) techniques and diverse datasets, public health surveillance of gut ailments can be enhanced to better understand and respond to health challenges globally [12 - 14].

AI-assisted public health surveillance is feasible across various aspects of public health initiatives [15]. Furthermore, it enhances public health by enabling culture-fair and education-independent automated cognitive assessments in low- and middle-income nations. Integrating AI into public health surveillance holds immense promise for improving disease estimates, enabling early warning of outbreaks, and safeguarding public health through proactive measures, by utilizing data from the Emergency Medical Communication Centre (EMCC) to enhance active and passive surveillance efforts.

GUT MICROBIOME-RELATED DISEASE SURVEILLANCE USING AI

The gastrointestinal microbiome is a multifaceted and evolving ecological system that is integral to human well-being and the cause of various diseases [16 - 18]. Concerning surveillance of gut microbiome health, AI advances technologies to analyze microbial genomes, predict host phenotypes, and suggest personalized nutrition strategies [19]. The gut microbiome's dynamic nature, influenced by diet and disease, can lead to dysbiosis, impacting the immune system and overall health [17, 20, 21]. AI generates individualized gut microbiota profiles and possesses the capability to analyze extensive and diverse datasets that are associated with the health impacts of a community. Machine learning classifiers offer valuable insights regarding the link between microbial communities and diseases. Table (1) summarizes the application of machine learning approaches in microbiome research.

Metagenomics empowered by an AI framework provides a powerful approach to investigating microbial diversity [31], their genes, and gene products. The function- and sequence-based [32] analysis has provided a significant advantage in diagnosing infections by directly analyzing samples obtained from humans or their surroundings [33, 34]. Several AI-centred computational tools have adapted problem-solving techniques, including mathematical optimization, artificial neural networks, statistical methods, and logistic regression. Bzhalava *et al.* trained an ANN to taxonomically categorize the metagenomic sequences into virus and non-virus classes with a receiver operating characteristic curve of 0.79; the reported

Table 1. ML application in microbiome analysis guided by available scientific information.

ML method	Microbiome Research	Reference	Citation
Supervised Learning – Logistic Regression (LR) analysis.	Selecting 300 biomarkers from 13,990 microbial features, which include clinical data and gene abundance matrices from 806 Chinese microbiomes, enables a large-scale disease screening population.	H. Wu <i>et al.</i> (2018)	[22]
Linear Discriminant Analysis (LDA).	Described statistics, pattern recognition, and deep learning in microbiome data analysis.	Y. H. Zhou and P. Gallins (2019)	[23]
K-Nearest Neighbors (k-NN).	Generated a model that effectively predicts the postmortem interval.	H. R. Johnson <i>et al.</i> (2016)	[24]
Naïve Bayes probabilistic classifiers.	Enhances the accuracy of taxonomic classification for the 16S rRNA gene sequences.	J. J. Werner <i>et al.</i> (2012)	[25]
Artificial Neural Network (ANN).	ANN platform for classifying host phenotypes from metagenomic data.	C. Lo and R. Marculescu, (2019)	[26]
Random Forest (RF) - ensemble learning.	Random Forest classifiers and the Least Absolute Shrinkage and Selection Operator (LASSO) are commonly utilized for feature selection and patient analysis stratification.	S. Yachida <i>et al.</i> (2019)	[27]
ML classifiers: SVM, LR, and Naïve Bayes.	Utility in Phy-PMRFI to demonstrate if phylogenetic relatedness accurately predicts functional similarity.	J. T. Wassen <i>et al.</i> (2019)	[28]
Bayesian Networks (BN).	Revealed an association between a specific taxon and enhanced therapeutic outcomes.	B. S. Jang <i>et al.</i> (2020)	[29]
Dynamic Bayesian Network (DBN).	DBN has been employed to examine longitudinal microbiome data sets to determine temporal correlations among various taxonomic levels and related clinical factors influencing the microbiome.	J. Lugo-Martinez <i>et al.</i> (2019)	[30]

accuracy was much higher than the chance level. The random forest has recently been preferred for its robustness and efficient classification, achieving more than 90% accuracy with 95% confidence [35, 36]. AI-driven integration of multi-omics data analysis provides comprehensive insights into the functional dynamics of the human gut microbiome and its impact on the host metabolism [37]. Recently, researchers at the Mayo Clinic have developed a computational tool called Gut Microbiome Wellness Index 2, which employs bioinformatics and machine learning methodologies to evaluate gastrointestinal health and track variations within the gut microbiome [38].

This book chapter explains how public health surveillance was used to treat gut microbiome-related diseases like obesity [39]. Public health officials are crucial in tackling this issue. The gut microbiome significantly influences obesity [40]. The gut microbiota composition varies between obese and lean individuals,

Advancements in Transformer-Based Models for NLP in Healthcare

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Abstract: Transformer-based models have transformed the branch of Natural Language Processing (NLP), significantly developing healthcare applications. This abstract examines the advancements and effects of these models in healthcare, emphasizing their strengths, obstacles, and future possibilities. Notable transformer architectures such as BERT and GPT, along with their variants, have greatly improved the proficiency of NLP systems in comprehending and producing human language. These models are particularly effective for tasks like named entity recognition, relationship extraction, and clinical text generation, which are essential for managing and interpreting large volumes of healthcare information. Their ability to be pre-trained on extensive datasets and fine-tuned with specialized medical information has allowed transformers to attain cutting-edge performance in medical coding, Electronic Health Record (EHR) analysis, and patient sentiment evaluation. Implementing transformer-based models in the healthcare sector has enhanced diagnostic precision, provided more tailored treatment suggestions, and improved patient engagement through chatbots and virtual assistants. For instance, models like BioBERT and ClinicalBERT, specifically fine-tuned on biomedical and clinical literature, have demonstrated notable advancements in interpreting and predicting medical conditions based on clinical notes. Nevertheless, several challenges persist, including concerns about data privacy, the necessity for extensive and varied medical datasets, and the interpretability of complex model predictions. Tackling these issues requires ongoing research on model transparency, privacy-preserving methods, and strategies to address the imbalance and variability in healthcare data. Looking ahead, transformer-based models are set to further revolutionize healthcare by facilitating more accurate and scalable solutions. Improvement in model design, training approaches, and domain-specific customizations will be vital for realizing their full potential to enhance healthcare outcomes and operational efficiency.

Keywords: Diagnostic precision, Electronic health records, Healthcare, Model predictions, Patient engagement, Transformer architectures, Virtual assistants.

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INTRODUCTION

Transformer models represent a significant advancement in deep learning architectures tailored for Natural Language Processing (NLP). They capture long-range dependencies, making them suitable for machine translation, text summarization, and question-answering [1]. The encoder-decoder framework is part of an architecture in which the encoder transforms the input into a compact summary while the decoder uses this summary to generate the output sequence. Both components are trained to minimize conditional log-likelihood, effectively allowing the model to handle input-output relationships [2].

The original transformer architecture features six identical layers in both the encoder and the decoder. Each encoder layer consists of two sublayers: a multi-head attention mechanism and a feed-forward network, enhanced with residual connections and layer normalization. The decoder adds a third attention layer that focuses on the encoder's output, with one layer masked to prevent future token visibility.

The transition to transformer models marks a pivotal shift from traditional sequential methods, like unidirectional RNNs and LSTMs, to attention-based architectures, thereby improving performance in NLP tasks [3]. Traditional models, including CNNs and RNNs, process data sequentially without revisiting previously processed tokens. While LSTMs improve RNNs by managing information flow through gating mechanisms, transformers leverage self-attention to capture dependencies more effectively [4].

Traditional deep learning models struggle with sequential reasoning, a capability enhanced by attention mechanisms. In human cognition, reasoning integrates and verifies facts through attention, effectively guiding the reasoning process by focusing on relevant information [5]. Similarly, in machine learning, tasks can be decomposed into specific subtasks that require concentrated attention on parts of the input or transformed data. This approach mimics the brain's neural processing, where attention helps manage information flow across multiple layers [6].

The Self-Attention Mechanism (SA) enables models to focus on important information while discarding less relevant details, which is particularly beneficial in computer vision by highlighting essential data for better outcomes. SA excels in establishing long-term dependencies within datasets, enhancing understanding of complex patterns. Multi-Head Self-Attention (MSA) processes multiple attention mechanisms simultaneously, capturing diverse data. This mechanism has notably improved neural machine translation through parallel computing, although the rise of large models often necessitates substantial computational resources [7]. In light of these developments, optimizing the sub-layers of

transformer models can enhance their inference rates. This paper advocates tailoring language model architectures to specific languages, suggesting that parameter adjustments may benefit various machine translation applications [1].

Uses of Transformer Models in Healthcare

Initially created for NLP (Natural Language Processing), transformer models have been adapted across various fields, including speech processing, multimodal learning, time series analysis, and remote sensing (Fig. 1). In healthcare, these models are employed across different data modalities, resulting in the development of modality-specific surveys focusing on areas such as medical imaging and biomedical language models. Large Language Models (LLMs) and

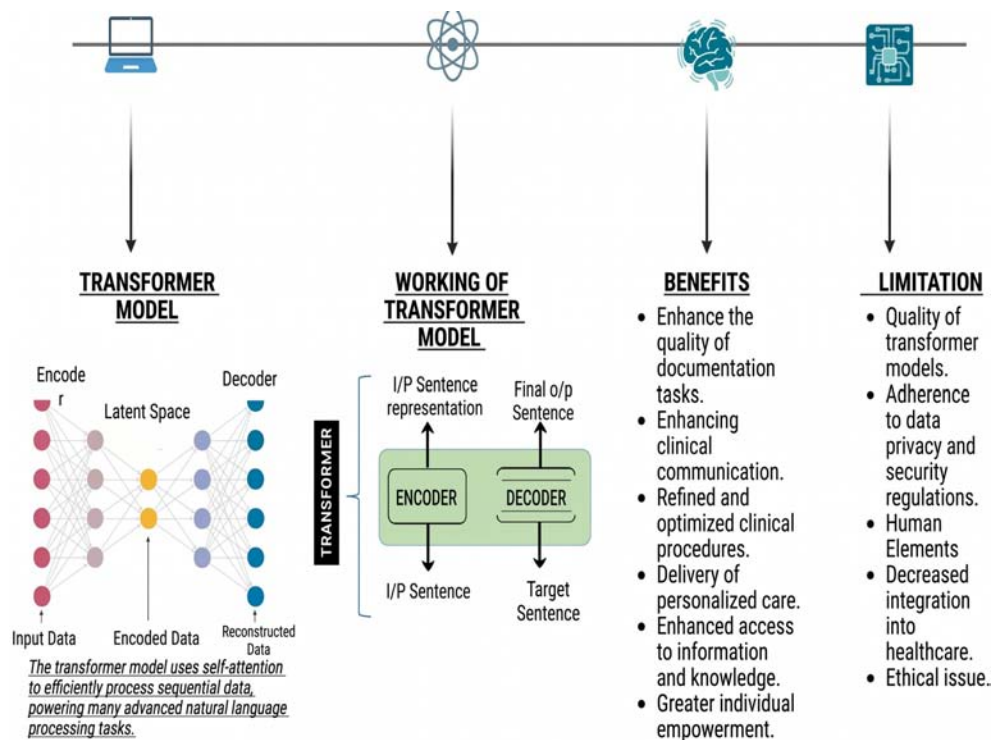


Fig. (1). Principles and architecture of transformer models.

transformers can revolutionize healthcare systems, significantly enhancing workflow management, clinical documentation, diagnosis, treatment, and communication. They facilitate personalized care, empower patients, and increase access to medical information. Despite this, their implementation comes with risks, including data-related issues, system impacts, quality and regulatory concerns, and economic implications requiring training programs to address shifts in the healthcare job landscape [6].

CHAPTER 14**Revolutionizing Mental Health Care with AI-Driven NLP Chatbots: Innovations, Applications, and Future Directions****Maharaja Muthuvairam Subbulakshmi¹, Manikandan Jayaraman¹, Pradeep Kumar Sriram¹ and Jeyaraman Jeyakanthan^{1,*}**¹ *Structural Biology and Biocomputing Lab, Department of Bioinformatics, Alagappa University, Karaikudi-630003, Tamil Nadu, India*

Abstract: The advent of modern technologies has revolutionized healthcare, introducing innovative solutions through Artificial Intelligence (AI), Deep Learning (DL), Machine Learning (ML), and the Internet of Things (IoT). These technologies have been leveraged to significantly enhance the quality of medical care. AI, particularly through ML and DL, automatically utilizes models derived from medical and biological data to improve decision-making and generate recommendations. For high-performance statistical tasks and input classification, Natural Language Processing (NLP) has been effectively employed to manage the healthcare sector. In natural language processing, chatbots have been utilized to implement NLP for various purposes, such as generating timely suggestions and alerts for patients in critical scenarios, particularly in mental health care. Traditional NLP chatbots, like Bidirectional Encoder Representations from Transformers (BERT), have been adapted for mental health applications, achieving an accuracy rate of approximately 98% with specialized terminology and personalized suggestions. The advancement of NLP techniques through AI-driven chatbots is expected to improve response generation for mental health issues and aid in developing technical solutions to reduce mental health problems within social populations. This chapter provides detailed insights into the development, advancement, and framework of NLP-associated chatbots in mental health. It covers technical aspects, performance metrics, implemented methodologies, case studies, real-time applications, drawbacks, and future perspectives. This chapter offers transformative information on NLP-driven technology for improving mental health care.

Keywords: Artificial Intelligence (AI), Deep Learning (DL), Machine Learning (ML), Medical chatbots, Mental health care, Natural Language Processing (NLP).

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INTRODUCTION

Incorporating futuristic technology, AI-ML (Artificial Intelligence and Machine Learning) has advanced healthcare informatics, paving the way for innovations in healthcare records, diagnosis, and treatment strategies. Implementing Machine Learning (ML) and Deep Learning (DL) algorithms has enabled AI models to process vast amounts of medical data and generate insights through an automated process, allowing AI to think and react like humans based on specific dependencies. This computerized task is decision-making, where AI assists healthcare professionals in reducing errors, improving accuracy, and providing personalized support. Furthermore, real-time monitoring of patients, which captures vital signs and parameters through connected devices, ensures that these data are continuously recorded and utilized to generate AI models for decision-making [1]. This synergy ensures that healthcare informatics is proactive rather than reactive, making it more predictive. Among its various impacts on healthcare, AI powers Natural Language Processing (NLP), a prominent area that allows machine models to interpret and understand human language patterns. NLP acts as a layer between humans and machine models, managing and understanding patients' queries, feedback, and clinical reports. With AI, NLP can analyze medical interventions and generate suggestions based on patient communication. One significant application of NLP is in medical chatbots, where users can chat or talk to the chatbot and obtain solutions to their queries around the clock. These conversational agents can seamlessly interact with users in natural language, assisting with diagnosis, scheduling appointments, and generating recommendations [2]. NLP medical chatbots have become a critical tool in mental healthcare, providing alerts with immediate responses and therapeutic interventions. Through meaningful conversations, these chatbots support users' queries on mental health conditions and offer instant guidance during critical moments. In mental health diagnosis, speech and text can be analyzed by NLP models, utilizing data from Electronic Health Records (EHRs) to detect conditions such as anxiety, depression, and schizophrenia. Emotion detection and sentiment analysis techniques are applied in conversations by extracting emotional cues that may signal mental health risks. Speech and voice patterns, such as tone, pitch, and prosody, are detected using NLP models combined with acoustic analysis, indicating cognitive decline [3].

NLP algorithms are built on a transformer model called BERT (Bidirectional Encoder Representations from Transformers), which constructs models in both forward and backward directions. This model is highly effective in recognizing linguistic markers of anxiety or depression using extensive datasets, enabling proactive interventions. The structured framework of BERT allows it to reach at-risk clients before their health conditions escalate [4]. This chapter explores

mental healthcare interventions through AI-powered NLP medical chatbots modeled with BERT, discussing innovations, applications, and future perspectives (Fig. 1).

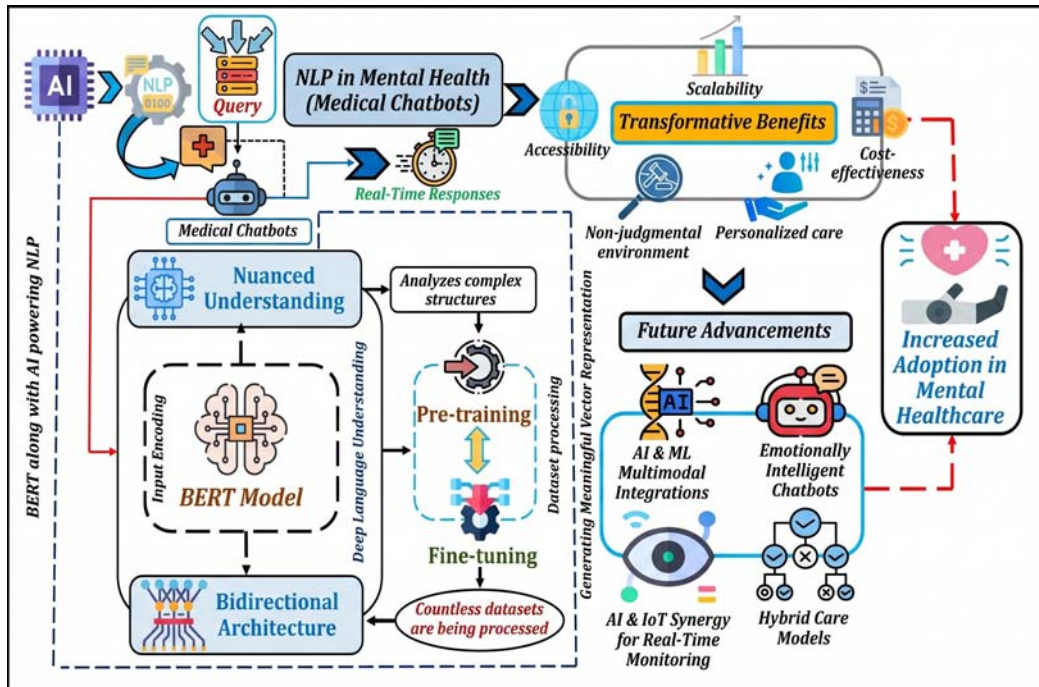


Fig. (1). Pictorial representation illustrating the workflow of AI-driven Natural Language Processing (NLP) medical chatbots.

ARCHITECTURAL FRAMEWORK OF NLP MEDICAL CHATBOTS

The Bidirectional Encoder Representations from Transformers (BERT) is an advanced model for sentence context analysis, revolutionizing NLP medical chatbots (Fig. 2). Through deep analysis, BERT captures words and their surrounding context in both left and right directions, making it exceptionally effective for language understanding tasks. This capability has been widely adopted in healthcare, enabling the development of medical chatbots with nuanced awareness [5]. BERT-based NLP medical chatbots demonstrate remarkable performance in comprehending the intricacies of mental healthcare terminology and conversations in a more informed and empathetic manner. BERT's latent ability to handle complex sentence structures and recognize the intent behind a client's query ensures accurate solutions, making these medical chatbots highly reliable in mental healthcare. This architecture processes input by encoding it into meaningful vector representations, generating contextually relevant solutions that are both medically appropriate and conversationally

Emerging Technologies in NLP for Healthcare

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Abstract: Emerging technologies in Natural Language Processing (NLP) are generating substantial breakthroughs across different sectors, notably in healthcare, where they are transforming patient care, diagnostics, and medical research. By utilizing the power of transformers and Large Language Models (LLMs) like GPT-3/4 and BERT, NLP is improving text production, contextual comprehension, and the interpretation of complex medical jargon. These technologies also evolve into multimodal applications, merging text with visuals and audio for thorough data processing. In banking and customer service, conversational AI leads to the development of sophisticated chatbots and emotion-sensitive systems. At the same time, explainable and ethical NLP provides openness and fairness in decision-making processes. Domain-specific models are being adapted to address the particular demands of specialized domains, and the combination of NLP with edge computing allows real-time processing for mobile and IoT devices. Moreover, NLP is breaking down language barriers with cross-lingual models, supporting low-resource languages, and encouraging inclusion. As these technologies continue to grow, they are establishing new norms in human-machine interaction, with substantial implications for tailored care, efficient operations, and new paths of discovery across numerous industries.

Keywords: BERT, GPT-3/4, Healthcare, Transformers, Large Language Models (LLMs), Natural Language Processing (NLP).

INTRODUCTION

From electronic health records to medical research publications, the healthcare sector faces a paradox in a time when digital information generation is unparalleled. While data has never been more plentiful, extracting actionable insights from this great ocean of information has never been more challenging. Emerging as a revolutionary branch of artificial intelligence, Natural Language Processing (NLP) is a critical tool for bridging this gap by giving sophisticated

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solutions to negotiate, assess, and exploit the complexity of medical information in inconceivable ways [1, 2].

In a contemporary hospital, a usual day comprises doctors dictating patient notes, radiologists writing thorough reports, nurses recording treatment events, and researchers reporting new clinical outcomes. Each of these endeavors provides valid but unstructured textual data. Designed for structured information, conventional data processing tools find it challenging to retrieve the intricacies, context, and linkages buried in these natural language descriptions [3 - 5]. This is where NLP technologies have become essential, as they are the intelligent link between computational analysis and human communication.

NLP has had an impact on healthcare in ways beyond simple text processing. NLP technologies radically alter healthcare delivery's critical components by enabling robots to perceive, interpret, and generate human language. From automating fundamental administrative tasks to recognizing tiny patterns in patient histories that may escape human observation, these technologies are increasing the efficiency and quality of healthcare services. Furthermore, in global health catastrophes like the COVID-19 pandemic, NLP's ability to swiftly scan and analyze enormous amounts of medical literature and clinical data has become increasingly crucial for hastening research and improving patient treatment choices.

As we stand at the intersection of artificial intelligence and healthcare, new NLP technologies are pushing the limits of what is attainable in medical practice. Advanced language models, driven by deep learning architectures, can now understand challenging medical tales with near-human accuracy. These computers can continually analyze several languages, adapt to expert medical jargon, and even recognize the contextual factors necessary for practical medical interpretation.

This chapter reviews developing NLP technologies in healthcare, examining their current uses and future potential. The progress of NLP from basic text processing to strong AI-driven systems capable of complex medical reasoning.

- Examines how cutting-edge NLP technologies are being applied to various parts of healthcare delivery, from clinical decision support to individualized patient care
- Investigates the problems and potential of adopting NLP technologies within healthcare settings
- Considers the ethical implications and privacy issues surrounding the employment of these technologies

- Explores new trends and future directions that promise to impact healthcare delivery radically

The impact of this technological discovery cannot be overstated. As healthcare systems worldwide face expanding demand, resource constraints, and a desire for improved patient outcomes, NLP technologies offer powerful tools to enhance the efficiency, accuracy, and accessibility of medical services. Understanding the use and implications of these evolving technologies is crucial for healthcare professionals, technologists, and legislators [6 - 10].

This chapter presents a detailed evaluation of the current state of NLP in healthcare and a forward-looking examination of developing trends and future potential. By evaluating these technologies' theoretical underpinnings and practical implementations, we aim to equip readers with a thorough knowledge of how NLP is revolutionizing healthcare and what we anticipate in the years ahead.

Historical Context: The Evolution of NLP in Healthcare

The route of natural language processing in healthcare reflects one of the most significant technical changes in medical informatics, moving from simple text processing systems to today's powerful artificial intelligence technology. This trend spans several decades, each distinguished by new technologies that profoundly modified how we handle and interpret medical information.

The narrative began in the 1960s, during what we now call the Rule-Based Era. This epoch witnessed the emergence of vital medical terminology standards with the invention of SNOMED (Systematized Nomenclature of Medicine). Early NLP systems mainly focused on pattern-matching algorithms and manually built rules to comprehend medical language. These basic systems employed regular expressions and Boolean logic to recognize medical terms and parse simple texts. The invention of MYCIN in the 1970s was a crucial milestone as one of the early medical expert systems, including rudimentary NLP capabilities. The Linguistic String Project (LSP) followed, pioneering systematic ways of medical language processing. While rigid rule-based architectures restricted these systems, they laid the fundamental basis for future developments.

The 1990s introduced the Statistical Revolution, signaling a paradigm shift in medical NLP. This period featured probabilistic models that could learn from data rather than depending only on predetermined rules. Hidden Markov Models have been developed as potent tools for medical entity recognition, whilst Maximum Entropy models have changed text categorization skills. The discovery of Conditional Random Fields enhanced sequence labeling skills, enabling more accurate processing of medical narratives. This decade also saw the integration of

Navigating the Future of Healthcare: Exploring the Next Phase in NLP

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Abstract: Natural Language Processing (NLP) uses modern machine learning techniques to help machines study human-understandable language. Innovations in NLP help change healthcare by being implemented in various domains of the healthcare sector. NLP can be used in domains such as making clinical decisions, enhancing patient care, and performing administrative tasks. Advances in deep learning methods, improved transformer models, and modern diverse datasets will open new horizons in the medical sector. However, challenges such as ethics and data privacy still remain. Exploring new areas that can be used in the healthcare sector, along with NLP, will give new ideas for research. This chapter examines the prospective utilization of NLP within the healthcare sector, elucidating its potential benefits for patients and healthcare providers. The discourse encompasses the foundational relevance of NLP, current implementation landscapes, key contemporary applications, anticipated future trends, inherent implementation challenges, the role of NLP in facilitating personalized medicine, and a prospective outlook for the technology's integration into healthcare systems.

Keywords: Clinical decision-making, Data privacy, Healthcare, Natural Language Processing (NLP), Transformer models.

INTRODUCTION

Natural Language Processing (NLP), a subset of Artificial Intelligence (AI), focuses on the interaction between computers and human languages. NLP enables machines to read, interpret, and derive meaning from unstructured data such as spoken conversations, handwritten notes, emails, and textual reports. Unlike structured data such as spreadsheets or coded data, which is easy for computers to analyze, unstructured data like clinical notes, discharge summaries, or pathology reports presents challenges due to its variability and ambiguity [1].

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The primary objective of NLP is to enable machines to understand language like humans, including understanding grammar, syntax, context, semantics, and intent. Various techniques, such as tokenization, part-of-speech tagging, named entity recognition (NER), sentiment analysis, and semantic parsing, are employed to understand and analyze language data. Recent advancements in NLP have been driven by complex machine learning models, like Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-trained Transformer (GPT), which are good at processing and generating natural text with perfect accuracy.

The new application of NLP in healthcare will bring significant changes using advanced AI techniques, mainly deep learning and transformer models. These technologies can be used to solve complex problems in healthcare. NLP can be used in multilingual patient communication, ensuring that all patients are cared for and understood correctly. However, as we adopt these technologies, we must address the important concerns that can come with this. Data privacy is a significant concern that should be taken care of. Sensitive patient information should be protected from unauthorized access, and ethical considerations should be considered. This chapter will explore how NLP is changing healthcare delivery and management. We will look at various new applications and discuss the current limitations of NLP technologies, including challenges in understanding context and the need for diverse training datasets. To move forward, we aim to show how NLP can become a key part of a more brilliant healthcare system. This will improve health outcomes, ensure that care is accessible and tailored to each patient's needs, and make a better tomorrow.

Relevance of NLP in Healthcare

The healthcare sector generates a significant amount of unstructured data daily. It can be a doctor's note, lab results, radiology reports, patient discharge summaries, or research articles. Early on, about 80% of these data lacked structure, which challenged analytics and decision-making. NLP can address this issue by uncovering unseen insights from this data, providing clinicians, administrators, and patients with better and more accurate information.

Below are some key areas where NLP plays an essential role in healthcare:

Clinical Documentation and Physician Burnout Reduction

Healthcare providers spend much time documenting patient information in Electronic Health Records (EHRs). NLP systems can automatically extract relevant

details from voice recordings or clinical notes. This helps workers reduce documentation burden, prevent burnout, and enhance the quality of care [2].

Enhanced Clinical Decision Support (CDS)

NLP is pivotal in analyzing and interpreting a patient's comprehensive health history alongside their current medical condition. By leveraging advanced algorithms, NLP systems can sift through vast amounts of medical literature, extracting relevant insights to provide tailored recommendations for each patient. For instance, these systems can propose individualized treatment plans or highlight potential drug interactions, enabling healthcare professionals to make more informed, real-time decisions. This capability not only aids clinicians in delivering personalized care but also enhances the overall quality of patient outcomes by ensuring that all relevant information is considered [3].

Improved Patient Outcomes and Experience

NLP improves patient outcomes by automating appointment scheduling, medication reminders, and mental health assessments. Additionally, sentiment analysis of patient feedback can help identify areas for improvement in care delivery, ultimately leading to higher patient satisfaction [4].

Public Health Surveillance

NLP algorithms play a crucial role in analyzing a wide range of data sources, including news articles, social media platforms, and other publicly available information, to effectively monitor disease outbreaks and discern trends in public health. A notable application of these tools emerged during the COVID-19 pandemic, where NLP was employed to sift through diverse datasets [5]. By identifying clusters of symptoms reported in various contexts, these algorithms significantly assisted health authorities in detecting potential outbreaks early and formulating timely responses. This proactive approach illustrates the power of NLP in enhancing public health surveillance and response strategies.

Automation of Administrative Workflows

NLP significantly enhances administrative workflows, particularly in insurance claims processing, denial management, and billing. By automatically extracting pertinent information from various documents, NLP minimizes the likelihood of errors, boosts operational efficiency, and speeds up the reimbursement processes.

SUBJECT INDEX

A

Area Under the Curve (AUC) 87, 117, 118, 119, 248
 Artificial Intelligence (AI) 52, 144, 151, 198
 Artificial Neural Networks (ANN) 55, 182, 221, 222
 Automated 25, 47, 227, 285
 appointment scheduling 285
 clinical note transcription 47
 machine learning (AutoML) 227
 speech recognition (ASR) 25

B

Bag of Words (BoW) 23, 24, 75
 Bayesian networks (BN) 179, 199, 206, 222, 227
 Bidirectional Encoder Representations from Transformers (BERT) 10, 24, 27, 59, 62, 63, 64, 65, 241, 243, 244, 245, 257, 258, 259, 260, 262, 269, 286, 297
 Bidirectional Long Short-term Memory (Bi-LSTM) 24, 95, 96, 97, 98, 99, 100, 101, 102, 103, 133
 Biomedical informatics (BMI) 11
 Biomedical Literature Mining (BLM) 11, 200
 Biomedical Text Mining (BTM) 80, 81, 122, 130, 134, 248

C

Clinical Decision Support (CDS) 11, 20, 21, 23, 24, 25, 270, 275, 276, 281, 282, 284, 298, 299, 302
 Clinical Decision Support Systems (CDSS) 7, 41, 70, 276, 284, 299, 311
 Cognitive Behavioral Therapy (CBT) 261, 263
 Compound-target Interaction (CPI) 11
 Computer-Aided Drug Design (CADD) 169, 170, 184

Conditional Random Fields (CRF) 23, 24, 26, 57, 62, 132, 133, 261, 262, 271
 Convolutional Neural Networks (CNNs) 10, 13, 24, 55, 56, 58, 63, 64, 65, 100, 223, 224

D

Data security and privacy 14, 29, 240, 241, 249, 281, 307
 Deep Learning (DL) 2, 4, 10, 11, 13, 23, 24, 25, 27, 54, 55, 66, 67, 179, 180, 182, 185, 198, 199, 205, 208, 212, 214, 257, 258, 261, 262, 270, 272, 274, 278, 296
 Drug-target Interactions (DTIs) 181, 202, 203, 205, 211

Dynamic Bayesian Network (DBN) 222

E

Electronic Health Records (EHRs) 10, 14, 25, 26, 31, 41, 58, 221, 245, 247, 251, 275, 281, 282, 301, 303, 308
 Emergency Medical Communication Centre (EMCC) 221
 Emotion detection 258, 262

F

False Positive Rate (FPR) 84, 87, 109, 117, 118, 248
 Fast Healthcare Interoperability Resources (FHIR) 31, 41, 281, 289, 308
 Federated learning 66, 67, 275, 291, 305, 306, 307, 312

G

General Data Protection Regulation (GDPR) 23, 26, 29, 41, 213, 241, 249, 264, 265, 307, 312
 Generative Adversarial Networks (GANs) 180, 184, 210

Generative Pre-Trained Transformer (GPT)
24, 27, 33, 38, 50, 236, 241, 242, 243,
244, 245, 297, 300

Genome-wide Association Studies (GWAS)
173, 174

H

Health Information Exchange (HIE) 23, 26,
245

Health Insurance Portability and
Accountability Act (HIPAA) 23, 26, 29,
39, 41, 213, 241, 281, 283, 289, 306,
307, 312

High-intensity Focused Ultrasound (HIFU)
146, 147, 148

High Throughput Screening (HTS) 175, 176

I

Inflammatory Bowel Disease (IBD) 221, 223,
224, 227

Inter-annotator Agreement (IAA) 74

Internet of Things (IoT) 249, 257, 266, 269,
292, 309, 310, 311

K

Knowledge discovery process 127, 129, 130

Knowledge graph 65, 133, 207, 208, 277

L

Large Language Models (LLMs) 80, 81, 82,
83, 90, 91, 132, 133, 238, 242, 269, 276

Least Absolute Shrinkage and Selection
Operator (LASSO) 222, 224

Ligand-based Drug Design (LBDD) 169, 177,
178

Long Short-term Memory (LSTMs) 24, 55,
57, 58, 64, 65, 95, 96, 100, 101, 103,
107, 132, 237, 261, 262, 272

M

Machine Reading Comprehension (MRC) 208

Machine Translation (MT) 7, 9, 25, 99, 103,
237, 238, 242, 243

Magnetic Resonance Imaging (MRI) 13, 71,
147, 149, 150, 151, 154, 188, 247, 272,
285, 286, 305

Medical Subject Headings (MeSH) 124, 125,
126

Multi-modal diagnosis 286

N

Named entity recognition (NER) 10, 20, 23,
24, 26, 56, 60, 61, 62, 63, 64, 65, 67, 73,
82, 91, 95, 96, 98, 126, 127, 129, 132,
133, 203, 207, 247, 248, 261, 262, 271,
274, 277, 278

Natural Language Generation (NLG) 7, 261

Natural Language Understanding (NLU) 7,
261, 262

O

Online Mendelian Inheritance in Man
(OMIM) 124, 125, 126, 212

Orphanet Rare Disease Ontology (ORDO)
125, 126

P

Papillary Thyroid Carcinoma (PTC) 90

Personal Health Records (PHRs) 23, 171

Principal Component Analysis (PCA) 199

Q

Quantitative Structure-activity Relationship
(QSAR) 178, 179

Question-answering (QA) 8, 10, 25, 237, 242,
248, 249

R

Receiver Operating Characteristic (ROC) 248

Reinforcement Learning (RL) 171, 181, 200,
227, 242, 261, 262

Role-based Access Control (RBAC) 290

S

Structure-based Drug Design (SBDD) 169,
176, 177, 180, 183, 200

Structure-based Virtual Screening (SBVS)
176, 185

Support Vector Machines (SVM) 63, 64, 179,
182, 183, 186, 199, 205, 222, 223, 261



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