Clin Schizophr Relat Psychoses
Volume 19:1, 2025

Clinical Schizophrenia & Related Psychoses

Commentary Open Access

Neuro-linguistic Programming for Mental Health: What the Future Holds for Clinical Study

Joydeep Sarkar*

Department of Physiology, Nanyang Technological University, Nanyang Ave, Singapore

Abstract

The current report has demonstrated the application of transformer based Natural Language Processing (NLP) model in identification (presence/absence) of complex symptoms of patients with Major Depressive Disorder (MDD). The model was specifically developed for identification of 3 symptoms: Anhedonia, suicidal ideation with intent or plan and suicidal ideation without intent or known plan. The NLP model was trained to clinical narratives of MDD patients obtained from progress notes at a specialty care institution. The model was able to demonstrate remarkable accuracy (both sensitivity and specificity) in the identification of said symptoms from verbose descriptions. Additionally, the report characterizes the robustness of the model to changes in the language, keywords etc.

Keywords: Anhedonia • Suicidal ideation • Natural Language Processing (NLP)

Introduction

The authors used a technique called triplet loss and focused the fine-tuning on generation of appropriate encoding output, rather than the final classification layer used. The transformer model used was BERT which is specifically focuses on encoding rather than the decoding part of transformer models (e.g., GPT). This is important as the goal of this work was not generation of new text but contextual language comprehension through generation of contextually meaningful embeddings. While the NLP model can identify sentences in a clinical note which are closely associated with the 3 symptoms, the authors have not tried to differentiate between symptoms present currently *vs.* mentions of historical symptoms or symptoms in a different person in the patient's life. Additionally, there is the risk of inconsistency in the symptoms captured in subsequent visits by different clinicians treating the same patient which will be highlighted by NLP models. The NLP model in the current report does not characterize the severity of the symptoms. Studies have shown that presence or absence of symptoms are only loosely predictive of overall disease severity [1,2]. A meaningful extension of the model would be to classify symptoms as absent, mild, moderate and severe. Of course, this will heavily depend on the level of detail available in the clinical notes in the EHRs. It is clear that more work is needed before the outputs of the NLP model can be directly used in impactful longitudinal clinical studies.

Looking beyond the specific limitations of the current report, the potential for application of these type of NLP models in the field of psychiatry clinical research is extensive [3]. The most immediate applications are around expansion of the NLP model to capture additional core symptoms of MDD (as defined by DSM V) and then expanding to the core symptoms of other major mental health disorders like Schizophrenia (SCZ), Attention Deficit Hyperactive Disorder (ADHD), Post-Traumatic Stress Disorder (PTSD) and Borderline Personality Disorder (BPD). There is growing interest in understanding real-world effectiveness of available treatments, burden of disease etc. in sub-cohorts of patients within diagnosis groups e.g., SCZ patients with cognitive impairment [4], predominantly negative SCZ patients, inattentive *vs.* impulsive vs combined ADHD etc. Lack of structured data in the real-world mental health practice is a major hurdle for clinical research focused on these cohorts. However, NLP derived symptoms will enable the development of such sub-cohorts from retrospective EHR-derived real-world data [5] changing the face of clinical research activities in mental health disorders.

Description

While discussing the future when unstructured data may be processed by NLP models and the information available at scale, it is essential that we highlight some of the immediate uses of such data.

***Address for Correspondence:** Joydeep Sarkar, Department of Physiology, Nanyang Technological University, Nanyang Ave, Singapore, E-mail: joydeep.sarkar@holmusk.com*

Received: 21 February, 2024, Manuscript No. CSRP-24-128014; **Editor assigned:** 26 February, 2024, PreQC No. CSRP-24-128014 (PQ); **Reviewed:** 12 March, 2024, QC No. CSRP-24-128014; **Revised:** 03 March, 2025, Manuscript No. CSRP-24-128014 (R); **Published:** 10 March , 2025

Clinicians will start to have the longitudinal trajectory of symptoms, function, etc. available in graphical format during a consultation. Identification of a trend or departure from one would become a lot easier and this will inevitably improve psychiatric care delivery.

The promise of the next decade in psychiatry is precision medicine-segmentation of patients into groups who are similar and defining care protocols unique to each such cohort. In the field of oncology, precision medicine has shown tremendous benefit with targeted therapies [6]. In the world of psychiatry, precision medicine will likely be driven by symptomology based segmentation and not by genetic biomarkers [7]. However, development of segments based on symptoms requires large volumes of data on patients with detailed longitudinal symptoms. NLP derived symptoms linked to structured data for the patients will greatly accelerate such research endeavors.

It goes without saying that detailed symptoms of patients will also be extremely useful in development of machine learning based predictive tools for better diagnosis or risk assessment. Integration of NLP models into the next generation of EHR systems can allow real-time validation of clinical documentation, predictive text making it significantly easier to document patient consultations while also providing consistent data capture.

In the last year, the world has seen the advent of Large Language Models (LLMs) which promise greater ability to comprehend textual information than the generation of models used in the report. However, these LLMs are not as efficient at identification of nuanced symptoms without significant training which is prohibitively expensive [8]. Additionally, it is unclear, whether use of LLMs will lead to significant improvement in the extraction of symptoms from clinical narratives discussed in the report.

Conclusion

Extraction of text and data from unstructured notes is not new, use of transformer models to identify complex symptoms and topics is relatively new [9]. Development of such models require a cross-functional team of data scientists and clinicians working very closely together. Labelled data generation by expert review is challenging for complex clinical concepts and suffers from significant interrater variations. Training of NLP models requires significant fine-tuning and understanding of how the language in the sentences correspond to the clinical concepts. Finally, the adoption of NLP-derived data in real-world studies will greatly depend on the clinical validation of such data done at scale by the researchers and data providers. Careful curation, cross-validation and regression testing of NLP-derived data to show validity, accuracy and reliability will go a long way in accelerating the adoption and acceptance of such data in clinical research [10,11].

References

1. Chen, Xieling, Haoran Xie, Gary Cheng and Leonard KM Poon, et al. "Trends and Features of the Applications of Natural Language Processing Techniques for Clinical Trials Text Analysis." *Appl Sci* 10 (2020): 2157.
2. Kulkarni, Deepali, Abhijit Ghosh, Amey Girdhari and Shaomin Liu, et al. "Enhancing Pre-Trained Contextual Embeddings with Triplet Loss as an Effective Fine-Tuning Method for Extracting Clinical Features from Electronic Health Record Derived Mental Health Clinical Notes." *J Nat Lang Process* 6 (2024): 100045.
3. Jones, Candace and Charles B. Nemeroff. "Precision Psychiatry: Biomarker-Guided Tailored Therapy for Effective Treatment and Prevention in Major Depression." *Adv Exp Med Biol* 1305 (2021): 535-563.
4. Malgaroli, Matteo, Thomas D. Hull, James M. Zech and Tim Althoff. "Natural Language Processing for Mental Health Interventions: A Systematic Review and Research Framework." *Transl Psychiatry* 13 (2023): 309.
5. Rangel, andres, Claudia Munoz, Maria V. Ocampo and Claudia Quintero, et al. "Neurocognitive Subtypes of Schizophrenia." *Schizophr Res* 43 (2015): 80-90.
6. Singhal, Karan, Shekoofeh Azizi, Tao Tu and S. Sara Mahdavi, et al. "Large Language Models Encode Clinical Knowledge." *Nature* 620 (2023): 172-180.
7. Yang, Johnny, Mary R. Nittala, Alexander E. Velazquez and Vedanth Buddala, et al. "An Overview of the Use of Precision Population Medicine in Cancer Care: First of a Series." *Cureus* 15 (2023).
8. Zhang, Tianlin, Annika M. Schoene, Shaoxiong Ji and Sophia Ananiadou. "Natural Language Processing Applied To Mental Illness Detection: A Narrative Review." *NPJ Digit Med* 5 (2022): 1-13.
9. Zhao, Mengge, James Havrilla, Jacqueline Peng and Madison Drye, et al. "Development of a Phenotype Ontology for Autism Spectrum Disorder by Natural Language Processing on Electronic Health Records." *J Neurodev Disord* 14 (2022): 32.
10. Zimmerman, Mark, Caroline Balling, Iwona Chelminski and Kristy Dalrymple. "Symptom Presence Versus Symptom Intensity in Understanding the Severity of Depression: Implications for Documentation in Electronic Medical Records." *J Affect Disord* 256 (2019): 344-347.
11. Zou, Kelly H, Jim Z. Li, Joseph Imperato and Chandrashekhar N. Potkar, et al. "Harnessing Real-world Data for Regulatory Use and Applying Innovative Applications." *J Multidiscip Healthc* (2020): 671-679.

How to cite this article: Sarkar, Joydeep. "Neuro-linguistic programming for mental health: What the future holds for clinical study." *Clin Schizophr Relat Psychoses* 19 (2025)