Deep Learning to Predict Harmful Neurological and Musculoskeletal Side Effects for Patients Receiving Long Term Opioid Treatment

Suranga Kasthurirathne PhD1,2, Shaun Grannis MD, MS1,2, Matthew Bair MD, MS1,2,3
1Indiana University, Indianapolis, IN, USA; 2Regenstrief Institute, Indianapolis, IN, USA; 3VA Health Services Research and Development Center for Health Information and Communication, Indianapolis, IN, USA

Introduction. Improper opioid prescribing patterns contribute significantly to the misuse and addiction to opioids. The Centers for Disease Control (CDC) in 2019 published guidance1 citing the need for better evidence on the benefits and harms of clinical decisions on opioid prescribing, including when and how to reduce opioid dosage for patients receiving Long Term Opioid Treatment (LTOT). As a majority of patients receiving LTOT present at primary care settings, the ability to make informed prescription decisions at primary care is particularly relevant. However, primary care providers lack appropriate decision tools to identify patients at risk of various harmful side effects associated with LTOT. We leveraged comprehensive longitudinal patient datasets to develop deep learning networks capable of predicting risk of various harmful side effects in patients undergoing LTOT.

Methods. We extracted comprehensive longitudinal medical data on patients presenting for primary care at Eskenazi Health systems of Indiana between 2016-2018 from the Indiana Network for Patient Care (INPC) a large, statewide Health Information Exchange (HIE). We leveraged medication records to identify a subset of adult patients undergoing LTOT. We also identified a variety of harmful side effects that impact patients undergoing LTOT. We prepared a gold standard for supervised learning by using International Classification of Disease (ICD) codes to identify occurrences of various side effects per each patient. Next, we prepared feature vectors representing a wide range of patient-level clinical, behavioral and past visit history data. Feature vectors were randomly split into train (60%), validation (20%) and test sets (20%). Train and validation datasets were used to train deep learning models to predict risks impacting selected biological systems using Keras, a python based deep learning library. We also applied early stopping to prevent overfitting of our models. To increase clinical accuracy, we only included clinical data reported prior to occurrences of the side effect under test. Each model was trained to optimize F1-Score, an accuracy measure representing the harmonic mean between precision and recall.

Results. We identified 72,484 adult patients who had received at least one primary care visit at Eskenazi health. Of these, 5,544 (7.65%) patients were identified as patients receiving LTOT. A total of 177 clinical, behavioral and demographic features were extracted from INPC data for machine learning. We elected to build deep learning models to predict side effects impacting neurological systems (confusion, delirium, hallucination, sedation, seizures) and musculoskeletal systems (fractures and falls) due to their higher prevalence (6.5% and 39.8% respectively), as well as their clinical value. Optimal deep learning models for predicting each outcome consisted of two hidden layers each. When tested on the 20% holdout datasets, each model reported F1-Score and Area Under the ROC Score values (AUC ROC) > 70%, and recall values > 95%.

Discussion. Deep learning models predicted harmful side effects associated with neurological and musculoskeletal systems with considerable accuracy. We hypothesize that these models can be integrated into primary care workflows by mimicking similar efforts to predict need of referrals to address various social risks2. However, further assessment is necessary to evaluate the feasibility, acceptability, and efficacy of these models at a primary care setting. Other next steps include leveraging clinical information contained in free-text medical datasets to augment the feature sets available for supervised learning, expanding predictions to cover side effects impacting other biological systems, and performing risk factor analysis to identify which features influenced each side effect. Further, we hypothesize that use of patient and population-level Social Determinants of Health (SDoH) may also impact decision model performance.

References