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Key Takeaways:

Machine Learning from Multimodal Patient Data: How can we get from bench to bedside faster?

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To date, ML/AI is not common in the clinical setting in Ontario hospitals. The only usage is in diagnostic assays where ML/AI was used to develop the assay (e.g. Oncotype Dx). Meaningful entry of ML/AI in clinical settings will be (and in some cases, already is) through medical devices, like imaging systems, cardiac monitors, microscopes, etc.

Current challenges to using AI in medicine in Ontario hospitals

- ***Silo-ed data layers.*** Each layer of data may be generated by a different provider, which then needs to be collected by a clinician who puts it together to help guide treatment. For instance, investigating the biology of a single patient's colon tumour could involve 3-4 pathology and molecular tests completed by different providers, with results entered into different laboratory databases; concurrent, multiple, unlinked entries may be made in the Patient Care System, which leaves a clinician needing to manually identify these separate records to decide on a patient's course of treatment.
- ***Silo-ed data across hospitals.*** Challenge in harmonizing and integrating clinical data sets. Challenge with ML/AI use directly within the clinical setting is that methodologies are not easily transferable to other clinical settings without retraining.
- ***Technical variability among institutions, lack of calibration standards.*** Challenge in technical variability if data requires calibration of clinical systems. ML models will need to factor in uncertainty into their predictions.
- ***Lack of gold standards:*** Challenge is pathologists do not have a gold standard/reference for evaluating predictive prognostic markers as these models are learning for the future.
- ***Poor problem formulation:*** Evaluating the useability of ML methods in the clinic must include evaluating whether the ML approach matches the

deployment scenario. For example, it is problematic if one is working with a certain type of cancer that is seen only 5% of the time in the clinic, but the ML model was evaluated on a 50%/50% negative/positive sample set - this is a mismatch.

- ***Data bias:*** Challenge in the inherent bias in clinical data which AI doubles down on and propagates

Opportunities on the Road Ahead

- **Establish best practices for the field in model design, performance reporting, and interpreting studies**
- ***Require due diligence in QC of model data:*** Appreciate tools for exploratory data analysis that ensure biological and technical variates have been controlled for. Make it a requirement in the field to present these data for model interpretation.
- ***Minimize sampling bias:*** Ensure that patients used for training models represent the model population.
- ***Understand reporting metrics:*** Understand the choice of reporting metric: e.g. AUROC is common but ignores class imbalance issues. Require reporting of other measures such as precision-recall.
- ***Temper the hype:*** We need to change the perception that AI is a magic bullet. Models are not trained once and deployed. Clinical models require continuing validation in larger and independent samples to increase confidence, as well as be evaluated for different population subgroups. e.g., ASCVD model calibrated for populations with different genetic ancestry.
- ***Reduce data bias:*** Understanding biases in data collection that are magnified by AI algorithms.
- Encourage more collaboration between machine learning model developers and clinical researchers in formulating the problem to reflect characteristics observed in the clinic, including class imbalance.

Panelists

- **Dr. Anne Martel,** Sunnybrook Research Institute, Senior Scientist (Machine learning in clinical imaging).
- **Dr. Michael Hoffman,** Princess Margaret Cancer Centre, Senior Scientist (Machine learning in genomics; liquid biopsy; member of Temerty Centre for AI Research and Education in Medicine)

- **Dr. Harriet Feilotter,** Queen's University, Professor, Dept of Pathology and Molecular Medicine (Clinical genomics; Ontario Health Data Platform).
- **Dr. Amber Simpson,** Associate Professor, Department of Biomedical and Molecular Sciences and School of Computing, Queen's University (Machine learning in clinical imaging; Ontario Health Data Platform).
- **Dr. Michelle Brazas (co-moderator),** OICR, Senior Program Manager.
- **Dr. Shraddha Pai (co-moderator),** OICR, Principal Investigator (Machine learning and genomics; member of Temerty Centre for AI Research and Education in Medicine).