Preventing Heart Failure Hospitalizations with Artificial Intelligence

Date: April 17th, 2020

Dr. Heather Ross MD, MHSc (Bioethics), FRCPC, FACC
Head, Division of Cardiology
Pfizer Research Chair in Cardiology
Loretta A. Rogers Chair in Heart Function
Site Lead, Ted Rogers Centre for Heart Research
Professor of Medicine
Peter Munk Cardiac Centre
Disclosure

- I have no relevant disclosures
Why do we want to predict risk of hospitalization…….to intervene sooner…….

- Mortality
- Quality of Life
- Cost
- Days lost from work/life

Risk Prediction Scores
Monitoring tools
Meta-Analysis Global Group in Chronic (MAGGIC) Heart Failure Risk Score

- N = 39,372 patients
- HFpEF, HFrEF
- Large international database from 30 cohort studies
- FU 2.5 years
- 13 clinical variables
- Purpose: predict mortality
- Multivariable piecewise Poisson regression methods with stepwise variable selection

Meta-Analysis Global Group in Chronic (MAGGIC) Heart Failure Risk Score

Pocock et al, EHJ 2013 34, 1404–1413
Systematic Review of Predictive models

Circles are mean C-statistic values for each model

RED = mortality
PURPLE = mortality/readm
GREEN = readmission

C-statistics for models predicting:
Mortality = 0.71
Mortality or HF hospitalization = 0.63
HF hospitalization = 0.68

Ouwerkerk et al, JACC HF 2014;2:429–36
Why do predictive models fail at such a high rate?

- Storage of data in medical silos prevents deployment and creation of algorithms
- Algorithms are **NOT** sufficiently transparent/explainable
- Algorithms are there but not used….
- Lack of **trust** of clinicians in predictions that are generated by algorithms

But most importantly….

- Predictive models are insufficiently predictive

© www.therecylcer.com
Data

1824-1907

If You Can't Measure It, You Can't Improve It

(William Thomson, Lord Kelvin)

1909-2005

"If you can't measure it, you can't improve it."

Peter Drucker

The promise of a healthy heart.
The complexity of medicine exceeds the capacity of the human mind.
ARTIFICIAL INTELLIGENCE
Programs with the ability to learn and reason like humans

MACHINE LEARNING
Algorithms with the ability to learn without being explicitly programmed

DEEP LEARNING
Subset of machine learning in which artificial neural networks adapt and learn from vast amounts of data
Learning Types

- **Supervised**
  - Algorithms use a dataset labeled to predict the desired and known outcome
    - Great for classification and regression problems
    - Time consuming
    - Requires labelling

- **Unsupervised**
  - Seeks to identify novel disease mechanisms, genotypes, or phenotypes from hidden patterns present in the data…
    - Find the hidden pattern without feedback from humans

- **Reinforcement**
  - A hybrid of supervised/unsupervised learning
    - Aim is to maximize the accuracy of algorithms using trial and error
Uses of AI: assisted, augmented, automatic AI

**Assisted AI**
Considered a weak form of AI and it is mainly used to automate simple tasks.

**Augmentation AI**
Support human decisions, rather than simulate independent intelligence.

**Automatic AI**
The final and most feared state of artificial intelligence; autonomous intelligence that can make decisions without human intervention.

https://www.tgdaily.com/technology/assisted-augmented-and-autonomous-the-3-flavours-of-ai-decisions
Clinical Application

A Remote Patient Monitoring Platform
Requirements to close the Circle of Home Management of Heart Failure

Many connections are required to allow for incorporation of physiological information obtained from patients at home to trigger interventions and potentially improve outcomes by means of heart-failure disease management.

Adapted from Desai and Warner Stevenson, NEJM 2010;363;24
Medly’s brain is a decision tree

- Designed to mimic clinicians decision making process
- Mathematical rules based algorithm can only handle a limited number of factors for decision
- Decision process tends to be conservative
  - can generate many false positives

Seto et al, JMIIR 2012 Jan-Feb; 14(1): e31
Clinical Outcomes

Limitations – pre and post analysis

Number of Hospitalizations

<table>
<thead>
<tr>
<th>Count</th>
<th>6 months before enrollment</th>
<th>6 months after enrollment</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.75</td>
<td></td>
<td>0.54</td>
</tr>
</tbody>
</table>

P < .001

Length of Stay (Days)

<table>
<thead>
<tr>
<th>Days</th>
<th>6 months before enrollment</th>
<th>6 months after enrollment</th>
</tr>
</thead>
<tbody>
<tr>
<td>8.42</td>
<td></td>
<td>6.3</td>
</tr>
</tbody>
</table>

Significant finding

Ware et al, J Med Internet Res 2020;22(2):e16538 doi: 10.2196/16538
Uses of AI: assisted, augmented, automatic AI

**Assistant AI**
Considered a weak form of AI and it is mainly used to automate simple tasks.

**Augmentation AI**
Support human decisions, rather than simulate independent intelligence.

**Automatic AI**
The final and most feared state of artificial intelligence; autonomous intelligence that can make decisions without human intervention.

https://www.tgdaily.com/technology/assisted-augmented-and-autonomous-the-3-flavours-of-ai-decisions
**CAVEATS**

Clinical trial not representative of broader race, age
Used prediction and not time to event analysis
Data was limited to that collected as part of the clinical trial

Angraaal et al, J Am Coll Cardiol HF 2020;8:12–21
Prediction of 30-Day All-Cause Readmissions in Patients Hospitalized for HF – ML vs. LR

Registry-based study linking patients from the Get With the Guidelines Heart Failure registry with Medicare data

Primary outcome: readmission within 30 days following discharge for index HF hospitalization

N = 56,477 patients

Age > 65

N - 250 variables

The study sample was randomly divided into training (70% of sample) and validation (30% of sample) cohorts

Use of ML algorithms did not lead to improved prediction of 30-day HF readmissions compared with traditional statistical models.

An ML analytics algorithm using continuous remote monitoring data from a wearable sensor will predict HF rehospitalization with ≥70% sensitivity at a specificity level of 85%.

87 completed 30 days
74 completed 90 days

Clinical alerts preceded hospitalization by a median time between 6.5 and 8.5 days

Stehlik et al, Circ Heart Fail. 2020;13:e006513
AI challenges

- HYPE?? AI winter
  - Disconnects between reality and expectation
- Biased data for AI model development
- What is our goal? Do we real expect CI = 1???
- Applying AI outside of populations represented in the training and validation sets
- Disregarding the ‘law of unintended consequences’
  - Impact on care or pt clinical relationship
- Limited data on ACTUAL effects on pt outcomes and cost of care

Matheny et al, JAMA 2020;323:509
Preventing Heart Failure Hospitalizations with Artificial Intelligence

Date: April 17th, 2020

Dr. Heather Ross MD, MHSc (Bioethics), FRCPC, FACC
Head, Division of Cardiology
Pfizer Research Chair in Cardiology
Lorretta A. Rogers Chair in Heart Function
Site Lead, Ted Rogers Centre for Heart Research
Professor of Medicine
Peter Munk Cardiac Centre