Can an Algorithm support Safe Practice?

Piyush Mathur MD, FCCM, FASA
Anesthesiologist & Intensivist
Department of General Anesthesiology & ICR
Quality Improvement Officer
Anesthesiology Institute
Cleveland Clinic
Founder, BrainX
Founder, BrainX Community
Disclaimers

• Founder, BrainX, LLC.

• Founder, BrainX Community, LLC.

• I am a physician
Algorithm definition: “a procedure for solving a mathematical problem (as of finding the greatest (common divisor) in a finite number of steps that frequently involves repetition of an operation”
Algorithms are not new to us…

https://aneskey.com/minimally-invasive-cardiac-output-monitor/
Have algorithms been safe?

* The algorithms employed within software of pulse oximeters are trade secrets and not open to scrutiny.

* We recommended that manufacturers collect data in Black patients to develop better calibration algorithms.


AI publications per speciality

Figure 2. Number of publications for artificial intelligence per speciality (per year)

https://aiforhealth.app
FDA approved AI algorithms
Can Algorithms guide safe clinician decision making?

*Timely alert confirmation by the provider was associated with:

- lower mortality ($P < 0.001$)
- improved SOFA progression ($P = 0.001$)
- lower median length of stay among survivors ($P = 0.001$).


Will clinicians follow algorithm’s guidance?

- Half of alerts were not followed by clinicians.
- When intervened by clinicians, guidance associated hypotension was decreased.
Can algorithms help with high skill decision making: Automated echocardiography

Fast and accurate view classification of echocardiograms using deep learning
Ali Madani1, Ramy Arnaout2, Mohammad Mofrad2 and Rima Arnaout1

Echocardiography is essential to cardiology. However, the need for human interpretation has limited echocardiography's full potential for precision medicine. Deep learning is an emerging tool for analyzing images but has not yet been widely applied to echocardiograms, partly due to their complex multi-view format. The essential first step toward comprehensive computer-assisted echocardiographic interpretation is determining whether computers can learn to recognize these views. We trained a convolutional neural network to simultaneously classify 15 standard views (12 video, 3 still), based on labeled still images and videos from 267 transthoracic echocardiograms that captured a range of real-world clinical variation. Our model classified among 12 video views with 97.8% overall test accuracy without overfitting. Even on single low-resolution images, accuracy among 15 views was 91.7% vs. 70.2–84.0% for board-certified echocardiographers. Data visualization experiments showed that the model recognizes similarities among related views and classifies using clinically relevant image features. Our results provide a foundation for artificial intelligence-assisted echocardiographic interpretation.

npj Digital Medicine (2018) 1:6; doi:10.1038/s41746-017-0013-1

Accuracy

~92-97% for AI

vs

70-84% for board-certified echocardiographers
Can algorithms democratize key skills?

Table 2. Comparison of Nurse-Acquired and Sonographer-Acquired Studies for Primary and Secondary Clinical Parameters

<table>
<thead>
<tr>
<th>Image No.</th>
<th>Clinical parameter examined by qualitative visual assessment</th>
<th>Nurse examination No. (%) [95% CI]</th>
<th>Sonographer examination No. (%) [95% CI]</th>
<th>Nurse-sonographer difference, percentage points</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Left ventricular size</td>
<td>232 (98.7) [96.3-99.7]</td>
<td>235 (100) [98.4-100.0]</td>
<td>-1.3</td>
</tr>
<tr>
<td>2</td>
<td>Global left ventricular function</td>
<td>232 (98.7) [96.3-99.7]</td>
<td>235 (100) [98.4-100.0]</td>
<td>-1.3</td>
</tr>
<tr>
<td>3</td>
<td>Right ventricular size</td>
<td>217 (92.3) [88.2-95.4]</td>
<td>226 (96.2) [92.9-98.2]</td>
<td>-3.9</td>
</tr>
<tr>
<td>4</td>
<td>Nontrivial pericardial effusion</td>
<td>232 (98.7) [96.3-99.7]</td>
<td>234 (99.6) [97.7-100.0]</td>
<td>-0.9</td>
</tr>
<tr>
<td>5</td>
<td>Right ventricular function</td>
<td>214 (91.1) [86.7-94.4]</td>
<td>226 (96.2) [92.9-98.2]</td>
<td>-5.1</td>
</tr>
<tr>
<td>6</td>
<td>Left atrial size</td>
<td>222 (94.5) [90.7-97.0]</td>
<td>234 (99.6) [97.7-100.0]</td>
<td>-5.1</td>
</tr>
<tr>
<td>7</td>
<td>Aortic valve</td>
<td>215 (91.5) [87.2-94.7]</td>
<td>228 (97.0) [94.0-98.8]</td>
<td>-5.5</td>
</tr>
<tr>
<td>8</td>
<td>Mitral valve</td>
<td>226 (96.2) [92.9-98.2]</td>
<td>233 (99.1) [97.0-99.9]</td>
<td>-2.9</td>
</tr>
<tr>
<td>9</td>
<td>Tricuspid valve</td>
<td>195 (83.0) [77.6-87.6]</td>
<td>217 (92.3) [88.2-95.4]</td>
<td>-9.3</td>
</tr>
<tr>
<td>10</td>
<td>Inferior vena cava size</td>
<td>135 (57.4) [50.9-63.9]</td>
<td>215 (91.5) [87.2-94.7]</td>
<td>-34.1</td>
</tr>
</tbody>
</table>

Can algorithms help do procedures more safely and effectively?

Fig. 1: Autonomous image-guided robotic vascular access, blood drawing and fluid delivery.

From: Deep learning robotic guidance for autonomous vascular access

Nature Machine Intelligence, volume 2, pages 104–115 (2020)

Can algorithms help us listen to our patients better? (15000+ comments analysis in less than one minute)

Can algorithms help improve safety event reporting?

**Cardiac Arrest**
- 1mg epinephrine IV
- Text string search: ventricular fibrillation, V. fib, chest compressions, pulseless electrical activity, PEA, cardiac arrest

**Hypotension**
- Mean arterial pressure < 65mmHg for cumulative time > 15 minutes for anesthetic time
- CMS QCDR approved metric

**Airway Event**
- Airway trauma
- Failed airway
- Esophageal intubation
- Laryngospasm
- Pneumothorax
- Bronchospasm
- Aspiration
- Unintended extubation

**Results**

![Bar chart showing cardiac arrests by month and status (Manual, Automated)](chart.png)

Unpublished data
## Table 1: Solutions for Effective Deployment of AI in Health Care

<table>
<thead>
<tr>
<th>Solution</th>
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<tbody>
<tr>
<td>Patient- and care-provider-centric—first do no harm</td>
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<tr>
<td>Clinician leadership</td>
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<tr>
<td>Rigorous model development and testing</td>
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<td>Explainable or Interpretable solutions—avoidance of black box</td>
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<tr>
<td>Clinical validation for generalizability and scalability</td>
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<tr>
<td>Cost-effective solutions</td>
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</table>
Evaluation framework - TEHAI

Figure 2  TEHAI checks during different phases. Three main phases including development, deployment and discernment phases with various subcomponents. TEHAI, Translational Evaluation of Healthcare Artificial Intelligence.
### Fig. 1 | Comparison of development pathways for drug therapies, AI in healthcare and surgical innovation

The colored lines represent reporting guidelines, some of which are study design specific (TRIPOD-AI, STARD-AI, SPIRIT/CONSORT and SPIRIT/CONSORT-AI); others are stage specific (DECIDE-AI and IDEAL). Depending on the context, more than one study design can be appropriate for each stage. §Apply only to AI in healthcare.

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Simulation of the selection problem. Columns, A and B, illustrate different data selection strategies. Upper panels show simulated mean arterial pressure (MAP; mmHg) values for samples corresponding to hypotensive events and nonhypotensive events. Lower panels are receiver operating characteristics curves showing MAP’s ability to discriminate hypotensive events from nonhypotensive events. The simulation is not an attempt to produce realistic data. It only serves to illustrate how the selection problem can result in a “skewed” receiver operating characteristics curve with very high specificity.
Conclusion

• Algorithms in anesthesiology or perioperative medicine are not new and are growing in use.

• Validation is important.

• Clinician leadership and collaboration with engineers is key.

• Evaluation frameworks are essential for successful and safe clinical implementation.

• Can algorithms help clinicians deliver safe care?
Can AI/algorithms save lives?

Failure is not an option.

— Gene Kranz —

email: mathurp@ccf.org