Online Learning of Medical Image Interpretation to a Performance Standard

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Disclosures

- ImageSim is an academic education platform that is hosted by the University of Toronto and the Hospital for Sick Children

- None of the investigators receive money from course fees

- Dr. Pecaric provides IT support for ImageSim and is married to Dr. Boutis; this financial relationship is managed by the University of Toronto

- Gratefully acknowledge a series of Medical Education Research Grants from the Royal College of Physicians & Surgeons of Canada, University of Toronto, and Hospital for Sick Children
Diagnostic Error

Surgical & Medication Errors

5% of outpatient office visits

10% of hospital inpatient deaths

18 MILLION diagnostic ERRORS each year

“Nearly every person will experience a diagnostic error in their lifetime.”

74,000 deaths each year

12% of hospital adverse events
Image Interpretation Errors

10-15% of medical images are misinterpreted by health care professionals. This can lead to mismanagement, patient harm, and medico-legal consequences.
Objectives

At the end of this session, you will be able to…

1. Discuss image set collection in service of defined educational goals
2. Compare different on-line models that teach image interpretation
3. Discuss methods for deriving competency setting standards
4. List education metrics for demonstrating visual diagnostic expertise
Learning Visual Diagnosis

Population of all images → Sample of images

Education Metrics ↓ Case Experience
Image Collection

Population of all images  Sample of videos/images

Educational Design & Standards

Case Experience
Image Collection

Population of all images

Sample of videos/images

Case Mix Variables
- Diagnoses with frequency of event
- Quality of images
- Patient demographics
- Physical exam features – e.g. skin type
- Clinical Significance
- Interpretation difficulty

Educational Design & Standards

Case Experience

Lee et al. Acad EM Educ & Training 2019
Image Set Collection – Sources

What are some ways to acquire images?
1. Expert collections
2. Digitally stored images taken during routine clinical operations
3. Crowdsourcing

Optic Glioma
Image Set Collection – Sources

Privacy and Institutional Considerations

1. Consent - conditions of waiver
   i. Not identifiable
   ii. Insurmountable
   iii. Reasonable person would consent
   iv. Public health benefit outweighs consent

2. De-identification

3. Data sharing agreements - legal
Image Set Collection - Variables

Can you think of what case and image-based variables would be relevant for an image set in your practice?
Image Set Collection - Variables

1. Sample size – total and minimums per diagnosis
2. Diagnostic range – ensure diagnostic sensitivity and specificity
3. Image quality
4. Participant demographics
Image Set Collection – Variables

- Numbers should be high enough that represent case diversity and rare but important cases and not subject to memorizing case solutions...hundreds

- Cases with and without pathology of interest
- Case number minimums - complexity, frequency, clinical importance

Boutis et al. CMEJ 2016
### Image Set Collection - Dermatology Example

<table>
<thead>
<tr>
<th>Morphological category (frequency of pathology in clinical setting), N=400*</th>
<th>Concerning Diagnoses, n/N=200. (%)</th>
<th>Not Concerning, n/N=200. (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vesiculo-bullous (25%)</td>
<td>Example 1, 2, …</td>
<td>Example 1, 2, …</td>
</tr>
<tr>
<td>Pustular (2.5%)</td>
<td>Example 1, 2, …</td>
<td>Example 1, 2, …</td>
</tr>
<tr>
<td>Dermatitis (25%)</td>
<td>Example 1, 2, …</td>
<td>Example 1, 2, …</td>
</tr>
<tr>
<td>Morbilliform (10%)</td>
<td>Example 1, 2, …</td>
<td>Example 1, 2, …</td>
</tr>
<tr>
<td>Papular/dermal (15%)</td>
<td>Example 1, 2, …</td>
<td>Example 1, 2, …</td>
</tr>
<tr>
<td>Purpuric (7.5%)</td>
<td>Example 1, 2, …</td>
<td>Example 1, 2, …</td>
</tr>
<tr>
<td>Papulosquamous (10%)</td>
<td>Example 1, 2, …</td>
<td>Example 1, 2, …</td>
</tr>
<tr>
<td>Vascular (5%)</td>
<td>Example 1, 2, …</td>
<td>Example 1, 2, …</td>
</tr>
</tbody>
</table>
# Image Set Collection - Dermatology Example

<table>
<thead>
<tr>
<th>Fitzpatrick Scale – Skin Type</th>
<th>Concerning Diagnoses, (n^*/N=200.) (%)</th>
<th>Not Concerning, (n^*/N=200.) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I - White</td>
<td></td>
<td></td>
</tr>
<tr>
<td>II - Beige</td>
<td></td>
<td></td>
</tr>
<tr>
<td>III – Light brown</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IV – Medium brown</td>
<td></td>
<td></td>
</tr>
<tr>
<td>V – Dark Brown</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VI – Black</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Demographics</th>
<th>Concerning Diagnoses, (n^*/N=200.) (%)</th>
<th>Not Concerning, (n^*/N=200.) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sex (male or female)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Image Quality (Scale 1-5)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Learning Visual Diagnosis

Population of all images

Sample of images

Education Metrics

Case Experience

Sample of images

Population of all images
Case Experience

Sample of images

Case Experience
15 year old boy presents with shortness of breath.
Can you think of examples of how image-based cases are presented on web-based education platforms?
Presentation of Images - Passive

- Uploading of images with descriptions and implications for management

https://www.orthobullets.com/
Presentation of Images – Active & Passive

- Small number of images with test set after education – assessment of learning

https://www.radiologymasterclass.co.uk/

https://www.medmastery.com/
Presentation of Images – Active

Assessment for Learning
Presentation of Images – Active

1. Cognitive Simulation

2. Deliberate Practice

3. Performance-based competency
Presentation of Images – Cognitive Simulation

Decision making – main educational outcome

Cases represent clinical practice and educational goals

History & Standard views

Pusic et al. Acad Med 2011
2 year old male fell from crib and not moving elbow.

A fracture/dislocation is...

- Definitely Absent
- Probably Absent
- Probably Present
- **Definitely Present**
- Locate Fracture/Dislocation

Submit
2 year old male fell from crib and not moving elbow.
Presentation of Images – Deliberate Practice

PEDiATRIC Elbow RADIOGRAPhS • CASE 5/392 • D0322(1127) • PRACTICE CYCLE 1/5

2 year old male fell from crib and not moving elbow.

FEEDBACK

Participant Response
Fracture/dislocation Present
Location

Case Description
There is displacement of both the anterior and posterior fat pads, consistent with a moderate large effusion. There is a subtle vertically oriented lucency in the medial aspect of the left distal humerus which may...

Read More
Show Markup
Show Target Dot
Show Text

Comment
Next Case

Accuracy 80.9%  Sensitivity 84.6%  Specificity 91.3%  Active Competency

Certified Competency Status
Presentation of Images - Performance Goal

Number of Cases Completed

Accuracy

90

Learner orient to system

△ = 25%

Initial

Final

Lee et al. AEM Educ & Training 2019
How do you decide on a competency standard?
Number of Cases Completed

Time Based
Competency Based

Sensitivity

Number of Cases Completed

Pusic et al. Acad Med 2015
Case Experience - Competency Standard

- Methods of competency setting in standardized test scores:
  - Delphi Method
    - Obtain consensus of experts through series of questionnaires
  - Norm-referenced standards (relative)
    - Comparing test-taker performance to other test-takers - e.g. Bell-curves
  - Criterion-referenced standards (absolute)
    - Measures test-takers against an absolute standard

Lee et al. AEM Educ & Training 2019
Clinical, academic and philanthropic goals:

1. Increase health care professionals’ accuracy in image interpretation

2. Support global access - subsidized access of our courses to health care providers who practice in the developing world

3. Conduct research and development that advances the learning of image interpretation

https://imagesim.com/
Learning Analytics

Martin Pusic, MD PhD

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Learning Visual Diagnosis

Population of all images → Sample of images

Education Metrics → Case Experience
Learning Visual Diagnosis

Population of all images

Sample of images

Educational Design & Standards

Participant Performance Metrics

Item-level Metrics

Learning Analytics

Case Experience
Learning Analytics for Visual Diagnosis

Person
- Accuracy – Sensitivity, Specificity…
- Behaviours – e.g. skipping views
- Time per case
- Confidence
- Coverage

Item/Case
- Cognitive model
- Sequential dependencies

Pecaric et al. Acad Med 2017
Learning Analytics for Visual Diagnosis

Person

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Item/Case

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Learning Analytics for Visual Diagnosis

Binary Decision Making

Diagnosis

Present

Absent
### 2 x 2 Table

<table>
<thead>
<tr>
<th></th>
<th>Significant Pathology</th>
<th>No Pathology</th>
</tr>
</thead>
<tbody>
<tr>
<td>User Says +</td>
<td>a</td>
<td>b</td>
</tr>
<tr>
<td>User Says --</td>
<td>c</td>
<td>d</td>
</tr>
</tbody>
</table>

- **a** and **b** are the counts for positive and negative cases, respectively.
- **c** and **d** are the counts for positive and negative predictions, respectively.
- **a+b** is the total count of positive cases.
- **c+d** is the total count of negative predictions.

**LR+** = \( \frac{a}{a+c} \)

**LR-** = \( \frac{d}{b+d} \)

**Sensitivity** = \( \frac{a}{a+b} \)

**Specificity** = \( \frac{d}{c+d} \)

Boutis et al. *Acad Med* 2010
Learning Analytics for Visual Diagnosis

Person

- Accuracy – Sensitivity, Specificity…
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- Coverage

Item/Case

- Cognitive model
- Sequential dependencies
8 year old male fell and twisted ankle. Lateral malleolar tenderness.
Subject Based Analyses

Item Based Analyses

Pecaric et al. Acad Med 2017
Learning Analytics for Visual Diagnosis

Person
- Accuracy – Sensitivity, Specificity…
- Behaviours – e.g. skipping views
- Time per case
  - Confidence
  - Coverage

Item/Case
- Cognitive model
- Sequential dependencies
Learning Analytics for Visual Diagnosis

Person
- Accuracy – Sensitivity, Specificity…
- Behaviours – e.g. skipping views
- Time per case

Confidence
- Coverage

Item/Case
- Cognitive model
- Sequential dependencies
8 year old male fell and twisted ankle. Lateral malleolar tenderness.
<table>
<thead>
<tr>
<th>2478 Errors</th>
<th>Definitely</th>
<th>Probably</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal Bias (False -)</td>
<td>46.3%</td>
<td>36.8%</td>
</tr>
<tr>
<td>Abnormal Bias (False +)</td>
<td>53.7%</td>
<td>9.4%</td>
</tr>
</tbody>
</table>

Learning Analytics for Visual Diagnosis

Person
- Accuracy – Sensitivity, Specificity…
- Behaviours – e.g. skipping views
- Time per case
- Confidence

Coverage

Item/Case
- Cognitive model
- Sequential dependencies
<table>
<thead>
<tr>
<th>Radiograph type</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td></td>
</tr>
<tr>
<td>Normal</td>
<td>131</td>
</tr>
<tr>
<td>Normal variant</td>
<td>15</td>
</tr>
<tr>
<td>Abnormal</td>
<td></td>
</tr>
<tr>
<td>Rule out Salter–Harris I fibula</td>
<td>36</td>
</tr>
<tr>
<td>Salter–Harris II fibula</td>
<td>7</td>
</tr>
<tr>
<td>Salter–Harris III/IV/V fibula</td>
<td>0</td>
</tr>
<tr>
<td>Salter–Harris I tibia</td>
<td>1</td>
</tr>
<tr>
<td>Salter–Harris II tibia</td>
<td>9</td>
</tr>
<tr>
<td>Salter–Harris III tibia</td>
<td>9</td>
</tr>
<tr>
<td>Salter–Harris IV tibia</td>
<td>5</td>
</tr>
<tr>
<td>Salter–Harris V tibia</td>
<td>0</td>
</tr>
<tr>
<td>Combined tibia/fibula</td>
<td>1</td>
</tr>
<tr>
<td>Other pathology—osteocondritis dissecans</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>234</td>
</tr>
</tbody>
</table>
Learning Analytics for Visual Diagnosis

Person
- Accuracy – Sensitivity, Specificity…
- Behaviours – e.g. skipping views
- Time per case
- Confidence
- Coverage

Item/Case
- Cognitive model
  - Sequential dependencies
Ankle Study

Frequency Plot of Item Locations (Difficulty)

Item Locations

Frequency Count (N=234)

Normal Cases

Abnormal

Boutis et al. CMEJ 2016;
Davis et al. Child Abuse Negl 2020
Learning Analytics for Visual Diagnosis

Person
- Accuracy – Sensitivity, Specificity…
- Behaviours – e.g. skipping views
- Time per case
- Confidence
- Coverage

Item/Case
- Cognitive model
- Sequential dependencies
Item Bank

Case 1
Item Bank

Case 1  Case 2
Item Bank
Item Bank

Case 1      Case 2       Case 3       Case 4       Case 5                        Case xx

Beckstead et al.  *Adv Health Sc Ed.* 2017
Yoon et al.  *Adv Health Sc Ed.* 2020
Cumulative Averaged Sensitivity for 12 Fellows

Mean Sensitivity vs. Number of Cases Completed

Points A, B, C, D indicate specific data points on the graph.
Educational Design

Data Flow Legend
1. Student generates inputs when interacting with content delivery component
2. Student inputs stored in student learning database
3. Predictive model fetches data from student and learning databases for mining
4. Mining results used by adaptive engine to adjust content delivery
5. Content flow to dashboard and various users for feedback and response via intervention engine
Learning Analytics for Visual Diagnosis

Person
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Item/Case
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Pecaric et al. Acad Med 2017
Summary

- Systematic approach to sets
- Cognitive models of the domain
- Learning analytics in a digital environment
- Competency standards
- Iterative adaptation by learner & system
Thank you

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References

https://imagesim.com/research-and-efficacy/
