Acute Respiratory Distress Syndrome (ARDS)  
- Develops in the lungs of critically ill patients and prevents effective gas transport  
- Leads to severely low blood-oxygen levels  
- Mortality rates associated with ARDS range from 26-58% in part due to an estimated 70% of cases being diagnosed late or not at all

**Hypothesis:** Accurate and early prediction of ARDS will lead to more timely diagnosis/treatment and better outcomes

**Goal:** a model based on routinely available electronic health record (EHR) data to predict onset of ARDS

**What is machine learning?**
- The study of tools & methods for identifying patterns in data.
- Patterns can then be used to either:  
  - increase our understanding of the current world (e.g., identify risk factors for a disease)  
  - make predictions about the future (e.g., predict who will get the disease).

**METHODS**

**Inclusion Criteria**
- Patients admitted in January-March 2016 who:
  - required >3L of supplemental O₂ for at least 2 hours
  - developed hypoxic respiratory failure

**Identifying Cases**
- Patients were reviewed for having ARDS by up to 6 clinicians
- Clinicians evaluated patients using the Berlin Definition

**Study Population**

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patients reviewed</td>
<td>383</td>
</tr>
<tr>
<td>Patients Diagnosed with ARDS</td>
<td>29</td>
</tr>
<tr>
<td>Percent Female</td>
<td>45.2</td>
</tr>
<tr>
<td>Median Age (years) [IQR]</td>
<td>62.0 [51.0 - 70.0]</td>
</tr>
<tr>
<td>Median length of stay (days) [IQR]</td>
<td>5.8 [2.9 – 6.0]</td>
</tr>
<tr>
<td>Median Time of ARDS diagnosis from admission (hours) [IQR]</td>
<td>44.5 [16.0 - 59.3]</td>
</tr>
</tbody>
</table>

**Comparison to Lung Injury Prediction Score (LIPS)**
- Only current clinical model for predicting development of ARDS
- LIPS has 22 variables (e.g. obesity, diabetes) with reported AUROC of 0.8

**EXPERIMENTS & RESULTS**

**Experiment 1**
- **Does our EHR-based model outperform the LIPS model?**

<table>
<thead>
<tr>
<th>Experiment</th>
<th>No. of features</th>
<th>Description</th>
<th>Median AUROC (95% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline EHR</td>
<td>884</td>
<td>EHR features</td>
<td>0.81 (0.59-0.93)</td>
</tr>
<tr>
<td>LIPS</td>
<td>1</td>
<td>LIPS score</td>
<td>0.73 (0.59-0.88)</td>
</tr>
<tr>
<td>LIPS+</td>
<td>22</td>
<td>LIPS features</td>
<td>0.65 (0.37-0.89)</td>
</tr>
</tbody>
</table>

**Experiment 2**
- **Do we need all six hours to make an accurate prediction?**

**Experiment 3**
- **Multiple Predictions Over Time**
  - A single prediction at 6 hours has limited clinical utility, how does the model perform when making multiple predictions over time?

**Take-Aways**
- EHR model outperforms the LIPS model in its given task while also utilizing data that can be automatically abstracted from the EHR
- EHR model has more clinical utility as it can make multiple predictions over a patient’s hospital stay

**Future Work**
- Time-varying parameters: Leverage the temporal aspects of our data through LSTMs to improve predictive performance of our model
- Learning latent feature representation: Use unsupervised learning and autoencoders to learn a new feature representation to improve predictive performance

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