Using Matlab to Develop Respiratory Disease Diagnostic Tools

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Acknowledgements

The technology used by ResApp Health has been and is continuously developed by Associate Professor Udantha Abeyratne at The University of Queensland.

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ResApp Health is developing the world’s first clinically-tested, regulatory-cleared respiratory disease diagnostic test and management tools for smartphones.

Diagnosis of respiratory disease is the most common outcome from a visit to the doctor.

Huge global market, 700M+ doctor visits annually for respiratory disease:
- Unique opportunity to integrate into telehealth providers’ existing platforms
- Strong demand also seen within clinics, emergency rooms and outpatient facilities
- Currently diagnosed using stethoscope, imaging (x-ray, CT), blood and/or sputum tests

→ Time consuming, expensive and not very accurate
Digital healthcare for respiratory disease

Respiratory disease diagnosis using only the sound of a patient’s cough

- The technology is based on the premise that cough sounds carry vital information on the state of the respiratory tract.
- We have taken a supervised machine learning approach to develop highly accurate algorithms which diagnose disease from cough sounds.
- In the next slide there is an example of a healthy cough and a pneumonia cough.
  - Can you guess which one is healthy and which one is pneumonia?
Two different coughs
Automatic respiratory disease diagnosis

- The system consists of two main parts:
- Front-end: finds cough sounds in a continuous audio stream
- Cough Analysis: provides a diagnosis based on learned cough signatures for various respiratory diseases

Audio stream → 1. Cough Detection → 2. Cough Analysis → Diagnosis

- Pneumonia
- Asthma
- Croup
- Bronchiolitis
- ...
Part 1: Detecting the coughs

- The front-end of the system finds the cough sounds in a continuous audio stream
- The cough detection system is able to filter out speech and other background noises
- The model has been trained with many hours of cough and non-cough sounds
Part 1: Detecting the coughs

Audio → Feature Extraction → Neural Network → Cough Detection

E.g. MFCC

Signal Processing Toolbox™ → Statistics and Machine Learning Toolbox™ → Cough Events
Audio features

- Audio features are calculated from the raw audio signal in processing windows.
- The audio features can be roughly divided into two categories:
  - Time domain features. E.g. Zero-Crossing Rate (ZCR)
  - Frequency domain features. E.g. Mel-Frequency Cepstral Coefficients (MFCC)
- Traditionally feature vectors are used instead of raw audio as input for ML algorithms.
  - Features reduce the dimensionality of the input.
  - Some features, like MFCC, approximates the human auditory system's response.
Audio features

E.g:
ZCR
MFCC

Feature Vectors

Processing frame
Feed-forward neural network

- Neural Network is a collection of artificial neurons
- Each neuron is a function of weighted sum of its inputs (+a bias).
- Number of the inputs equals to the number of features in the feature vector
- One can have any number of hidden layers and any number of nodes in each layer
Example of detecting a cough

1. Audio Signal
2. Probability output of a neural network
3. Detected coughs
Part 2: Analysing the coughs

- The cough sounds are fed into the analysis part
- It extracts various audio features for each cough
- The features are then fed into previously trained logistic regression models and classified into diseases or control classes
- Each model is a binary classifier (control vs. disease). I.e. the approach is so called one vs. many
- Number of coughs are used per diagnosis to increase the accuracy of the diagnosis
Part 2: Analysing the coughs

Cough Audio → Feature Extraction → Logistic Regression Models → Diagnosed Disease

- Signal Processing Toolbox™
- Statistics and Machine Learning Toolbox™
Easy to use, instant diagnosis using only a smartphone

- The algorithms are developed using Matlab™
- The final algorithms are deployed on various smartphone platforms
- The end-to-end diagnosis runs real time on a phone
- Easy to use
Verified by compelling pediatric clinical evidence

<table>
<thead>
<tr>
<th>Breathe-Easy Study Pediatric Results</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pneumonia vs. no respiratory</td>
<td>100%</td>
<td>95%</td>
<td>97%</td>
</tr>
<tr>
<td>Asthma vs. no respiratory</td>
<td>97%</td>
<td>92%</td>
<td>95%</td>
</tr>
<tr>
<td>Bronchiolitis vs. no respiratory</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Croup vs. no respiratory</td>
<td>94%</td>
<td>100%</td>
<td>99%</td>
</tr>
<tr>
<td>URTI vs. no respiratory</td>
<td>100%</td>
<td>95%</td>
<td>96%</td>
</tr>
<tr>
<td>Pneumonia, croup or bronchiolitis vs. URTI(^4)</td>
<td>89-100%</td>
<td>90-95%</td>
<td>89-98%</td>
</tr>
<tr>
<td>Differential diagnosis of pneumonia, croup, URTI and bronchiolitis</td>
<td>91-99%</td>
<td>89-98%</td>
<td>89-98%</td>
</tr>
</tbody>
</table>
## Breathe-Easy Study Adult Results

<table>
<thead>
<tr>
<th>Condition 1</th>
<th>Condition 2</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>COPD vs. no respiratory</td>
<td>100%</td>
<td>96-100%</td>
<td>98-100%</td>
<td></td>
</tr>
<tr>
<td>Asthma vs. no respiratory</td>
<td>91%</td>
<td>91-93%</td>
<td>91-92%</td>
<td></td>
</tr>
<tr>
<td>Pneumonia vs. no respiratory</td>
<td>97-100%</td>
<td>100%</td>
<td>98-100%</td>
<td></td>
</tr>
<tr>
<td>URTI vs. no respiratory</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>Asthma vs. COPD</td>
<td>93%</td>
<td>96%</td>
<td>94%</td>
<td></td>
</tr>
<tr>
<td>Pneumonia vs. Asthma</td>
<td>92%</td>
<td>81%</td>
<td>88%</td>
<td></td>
</tr>
<tr>
<td>Pneumonia vs. COPD</td>
<td>92%</td>
<td>92%</td>
<td>92%</td>
<td></td>
</tr>
</tbody>
</table>
The simplest model that fits the data is also the most probable model (Occam’s razor).

Why is simple better:
- There are fewer simple hypotheses than complex ones. If we manage to fit a less likely model (i.e. a simple one) it is more significant than fitting a complex model.
- If our in-sample error rate is very small, but out-of-sample error rate is big, our model is too complex for the given data. The model has learned the data too much (overfit).
Machine learning: Lessons learned

- Partition your data into **three** sets
  - **Training set** (>70%)
    - train your model with this data
  - **Dev set** (<15%)
    - tune your parameters with this data
  - **Test set** (<15%)
    - estimate your accuracy with this set
    - Don’t over use the test set. For example, if you run 100 different experiments and test them with the same test and then pick the best result. This result is not a good estimate anymore for the out-of-sample error rate
Machine learning: Lessons learned

- Use single number evaluation metric:
  - Helps you quickly evaluate algorithms and models, and therefore iterate faster
  - For example use F1-score instead of recall and precision.
- Analyse error systematically
  - Categorise the errors and find the single reason that contributes most to the error rate
  - Start addressing the error sources from the most significant one
  - For example: with the cough detection we found that cries were a prominent source of false positives