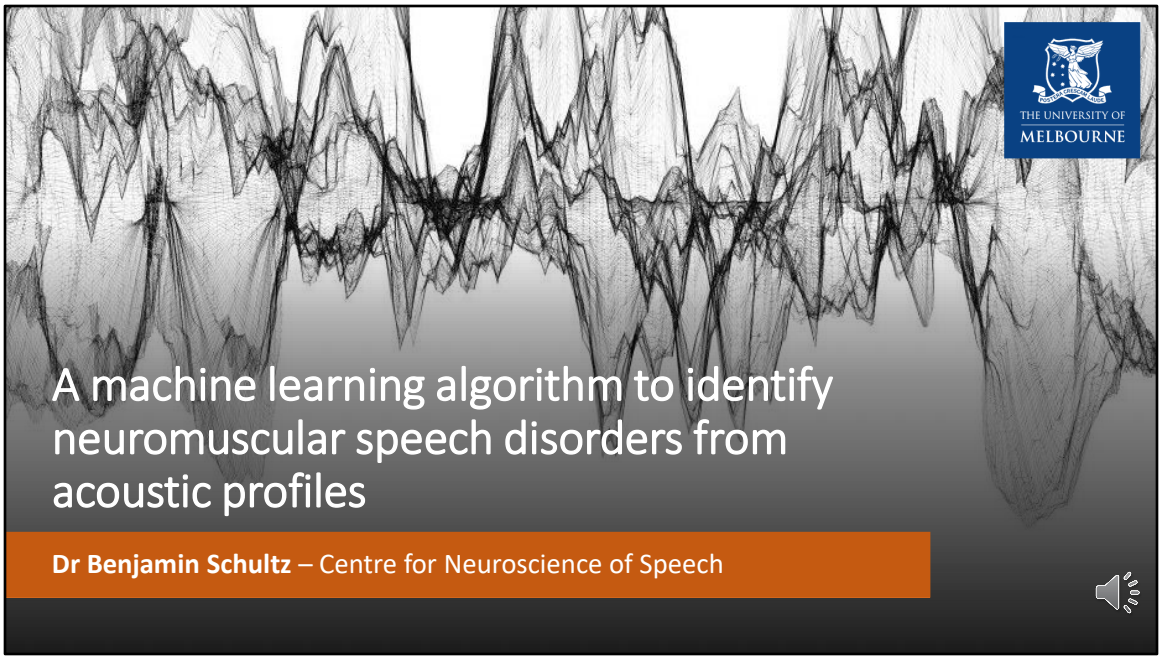
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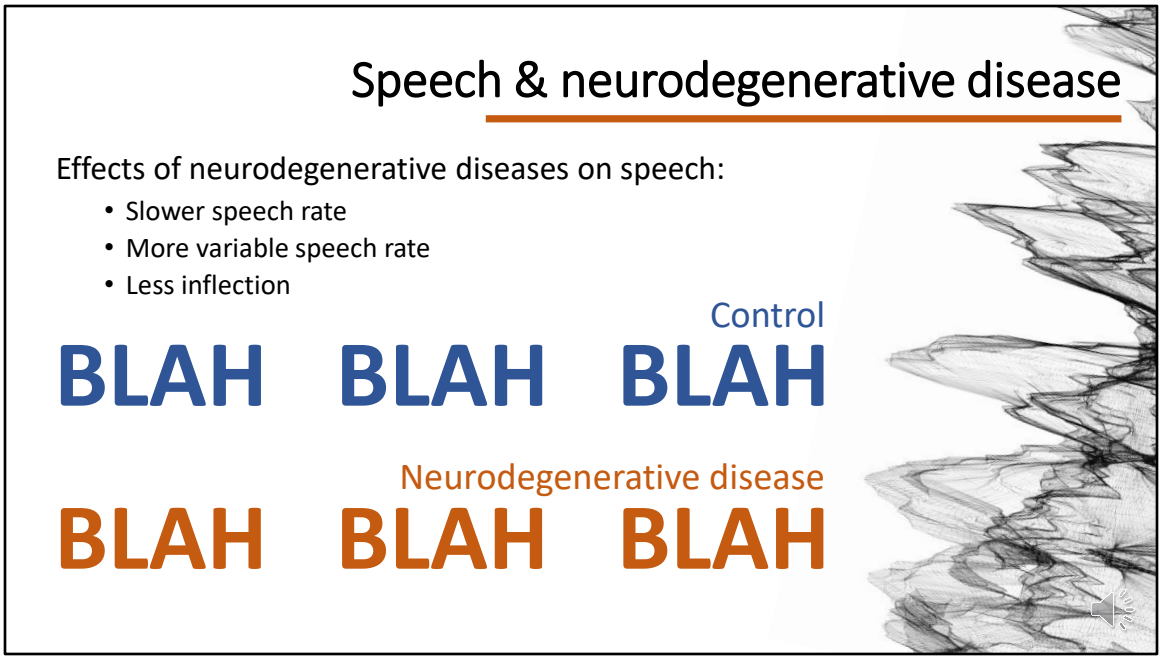
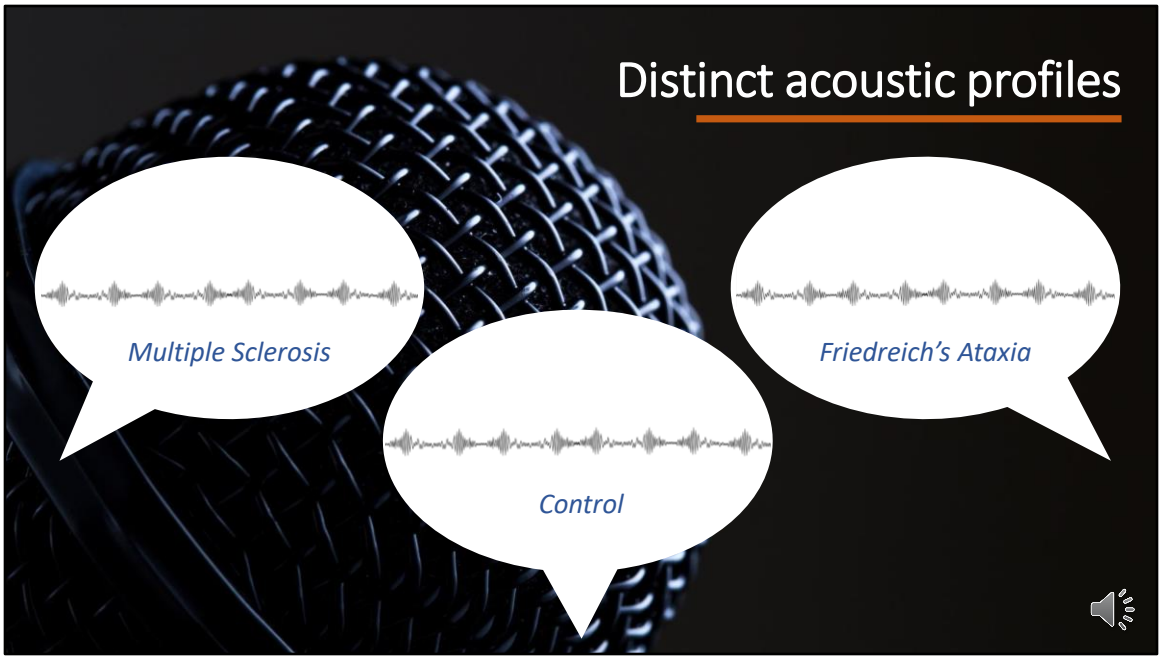
A machine learning algorithm to identify neuromuscular speech disorders from acoustic profiles
Dr Benjamin Schultz – Centre for Neuroscience of Speech



Speech changes as neurodegenerative diseases progress.

Although these effects may differ between diseases, it is common to see:

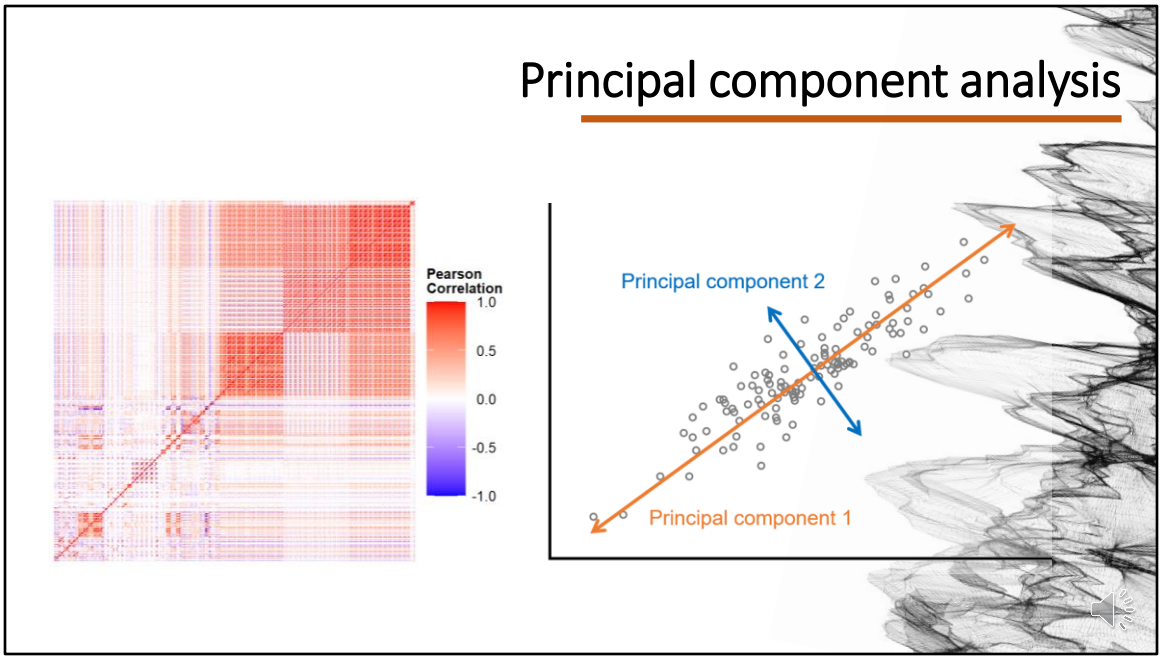
1. A slower and more variable speech rate,
2. Less inflection, perceived as monotone and inexpressive speech



These changes in speech can be objectively measured through acoustic analysis

For example, we can compare the speech of healthy speakers with people with MS or Friedreich's ataxia.

By constructing acoustic profiles of these groups, we can detect potential signatures of neurodegenerative disease.



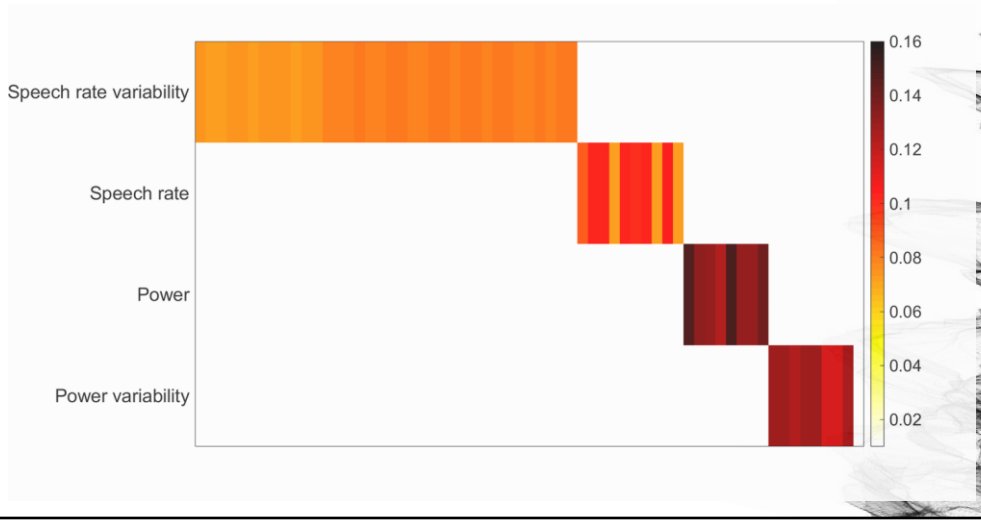
We used a large range of acoustic features that may overlap.

As shown in the correlation table to the left, many of the features were highly correlated.

Therefore, we used PCA to reduce redundancy and construct composite variables.

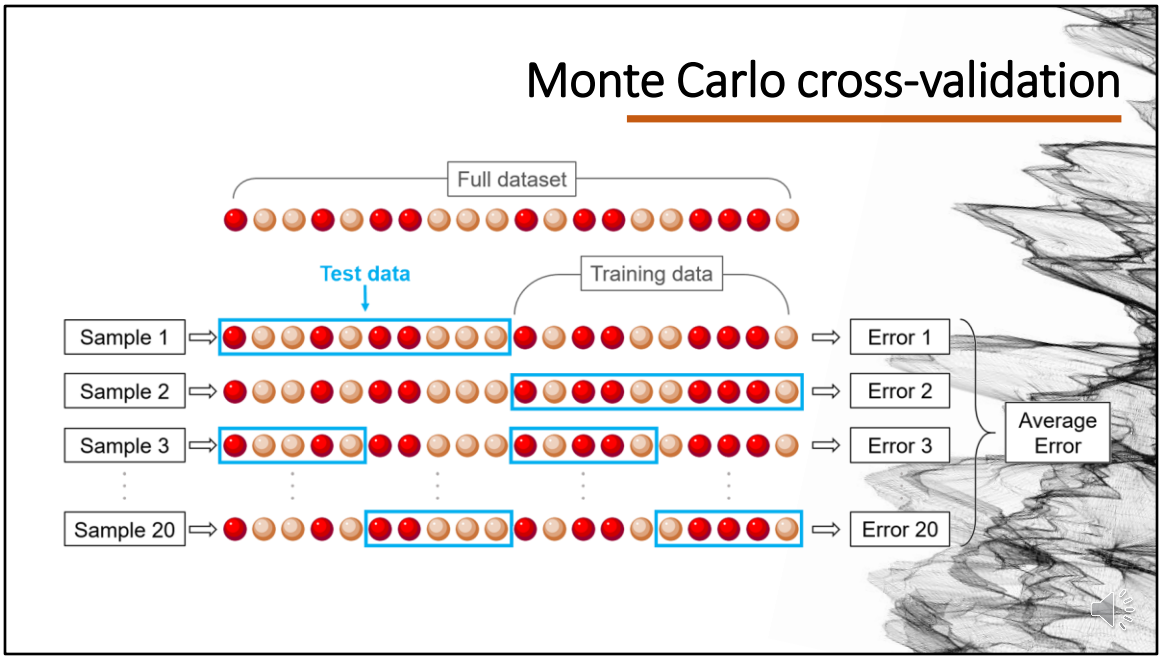
These composite variables reflected overarching themes for groups of variables.

Principal component analysis



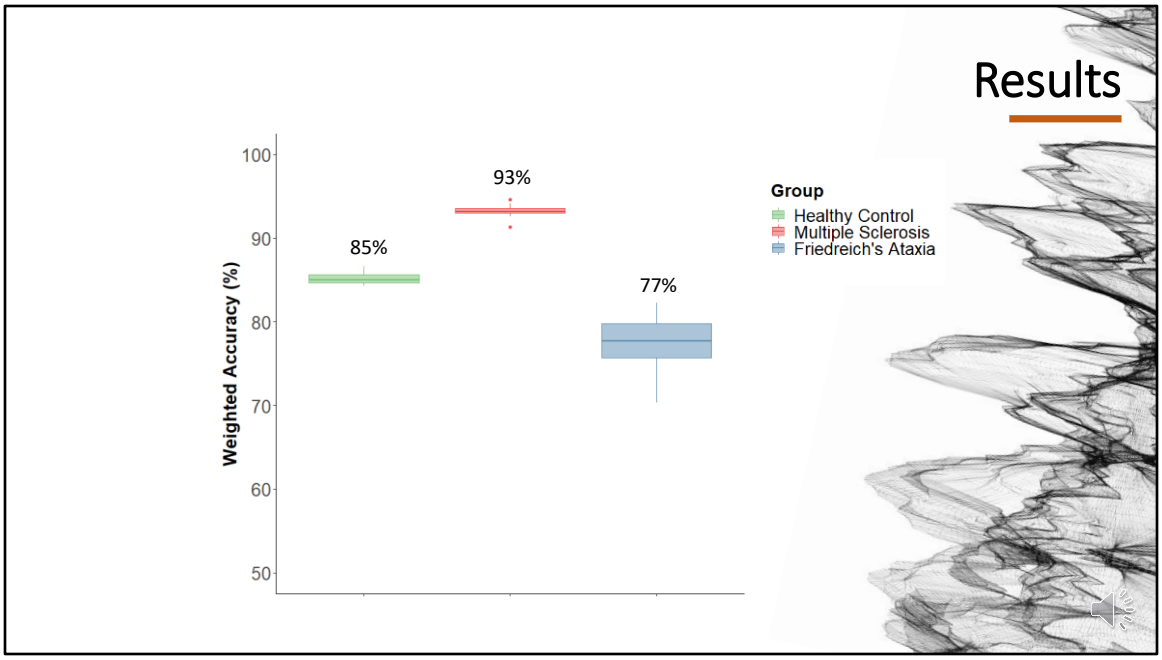
PCA revealed 184 components that explained 99% of variance in the acoustic features.

The four components that explained the largest proportion of variance in the acoustic features were speech rate variability, speech rate, acoustic power (often linked with loudness), and acoustic power variability. All components were subjected to machine learning using SVM.



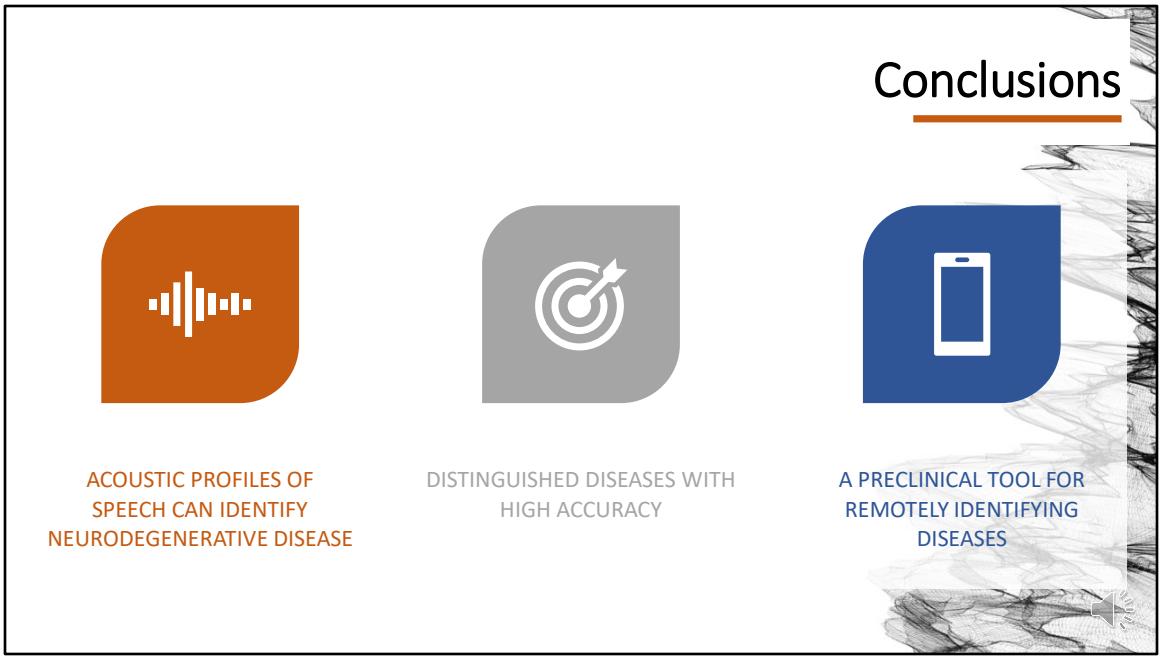
To ensure machine learning outcomes were reliable, we used Monte Carlo cross-validation techniques.

The SVM was trained on random selections of half of the data, and tested using the remaining half. This was repeated for 20 randomly selected samples. This allowed us to determine the error surrounding model performance for the three groups.



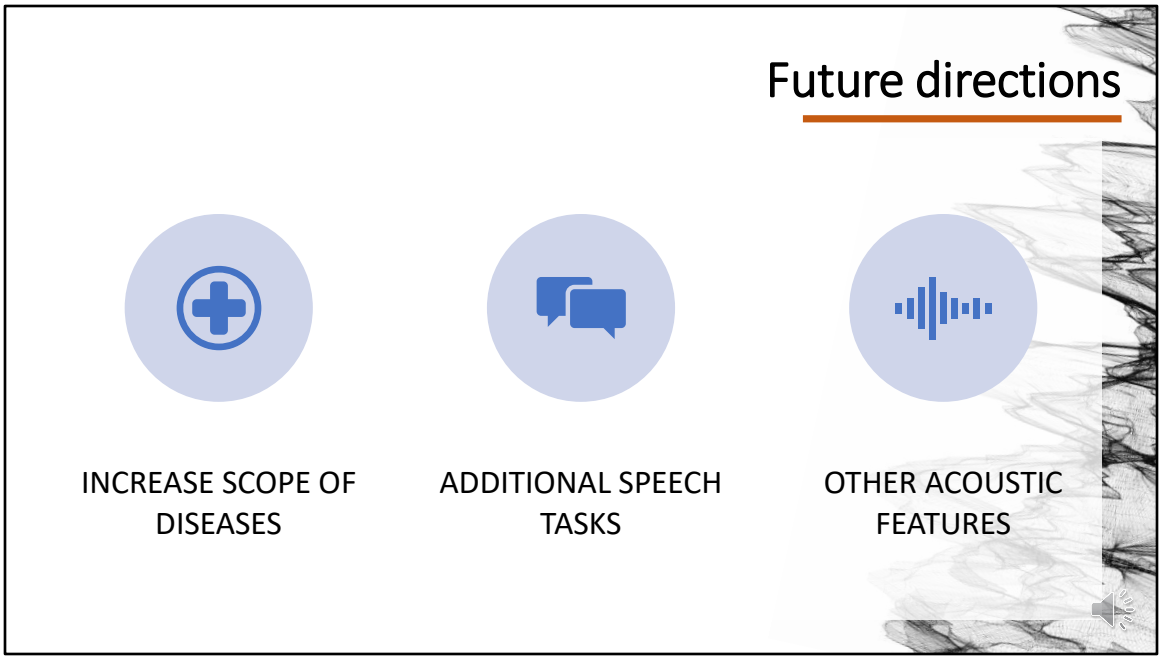
Results showed that all three groups could be accurately identified significantly above chance (33%; all *ps* < .001).

Classification accuracy was highest for multiple sclerosis, followed by healthy controls, then Friedreich's ataxia. Overall accuracy was approximately 85%.



We used acoustic profiles to identify two different neurodegenerative diseases, and distinguish these from healthy controls. To our knowledge, this is the first study to simultaneously delineate two different conditions using machine learning.

These high levels of accuracy suggest that machine learning of acoustic profiles could potentially be used as preclinical tools for remotely identifying diseases and signal to health professionals when further tests might be required.



To improve the power of these tools, we first need to increase the scope of diseases. This would increase our ability to distinguish diseases that may have subtle differences in their acoustic profiles. For example, we could examine Parkinson's disease, Huntington's disease, and dementia.

We could also examine different additional speech tasks that are more ecologically valid, such as, spontaneous speech.

Finally, there might be other acoustic features that would increase the classification accuracy, such as, voice onset time.

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