

Submission ID #: 68222

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Project Page Link: https://review.jove.com/files_upload.php?src=20807758

Title: Machine Learning-Based Cough Tone Classification: Diagnostic Exploration of Chronic Obstructive Pulmonary Disease and Respiratory Tract Infections

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Author Questionnaire

- 1. Microscopy:** Does your protocol require the use of a dissecting or stereomicroscope for performing a complex dissection, microinjection technique, or something similar? **No**
- 2. Software:** Does the part of your protocol being filmed include step-by-step descriptions of software usage? **Yes**
- 3. Filming location:** Will the filming need to take place in multiple locations? **No**

Current Protocol Length

Number of Steps: xx

Number of Shots: 24

Introduction

Videographer: Obtain headshots for all authors available at the filming location.

- 1.1. **Xiaohan Liu:** This research focuses on acoustic diagnostics, utilizing voice signal analysis and machine learning to extract distinctive voice features for non-invasive early classification of Chronic Obstructive Pulmonary Disease and Respiratory Tract Infections.

1.1.1. INTERVIEW: Named talent says the statement above in an interview-style shot, looking slightly off-camera.

What are the most recent developments in your field of research?

- 1.2. **Xiaohan Liu:** The recent developments in this field include AI-driven voice analysis, machine learning techniques such as Convolutional Neural Networks and Support Vector Machines, signal processing tools like MFCCs, and wearable acoustic sensors for detecting disease-related patterns in sound signals.

1.2.1. INTERVIEW: Named talent says the statement above in an interview-style shot, looking slightly off-camera.

What are the current experimental challenges?

- 1.3. **Xiaohan Liu:** One of the main challenges in the clinical translation of voice-based diagnostics is data scarcity. Other challenges include limited model generalization, privacy-ethics conflicts, and barriers to interpretability.

1.3.1. INTERVIEW: Named talent says the statement above in an interview-style shot, looking slightly off-camera.

Videographer: Obtain headshots for all authors available at the filming location.

Testimonial Questions (OPTIONAL):

How do you think publishing with JoVE will enhance the visibility and impact of your research?

1.4. **Xiaohan Liu:** (authors will present their testimonial statements live)

1.4.1. INTERVIEW: Named talent says the statement above in an interview-style shot, looking slightly off-camera.

Can you share a specific success story or benefit you've experienced—or expect to experience—after using or publishing with JoVE? (This could include increased collaborations, citations, funding opportunities, streamlined lab procedures, reduced training time, cost savings in the lab, or improved lab productivity.)

1.5. **Xiaohan Liu:** (authors will present their testimonial statements live)

1.5.1. INTERVIEW: Named talent says the statement above in an interview-style shot, looking slightly off-camera.

Ethics Title Card

This research has been approved by the Ethics Committee of Beijing University of Chinese Medicine and its Third Affiliated Hospital

Protocol

2. Data Analysis to Distinguish Patients with COPD from those with RTI

Demonstrator: Xiaohan Liu

2.1. After assembling the vocal feature indicator database, open SPSS (*S-P-S-S*) and load the appropriate data file [1]. From the menu bar, select **Analyze**, then choose **Nonparametric Tests**, followed by **Legacy Dialogs**, and click on **2 Independent Samples** [2].

2.1.1. WIDE: Talent seated at a computer, opening SPSS and loading the dataset file.

2.1.2. SCREEN: 2.1.2-SCREEN.mp4: 00:05-00:15

2.2. In the pop-up dialog box, select the observed variables to be compared under the Test Variable List section [1]. Then, under Grouping Variable, select the variable that will be used for grouping [2]. Click the **Define Groups** button and enter the identifiers for the two groups in the pop-up window [3].

2.2.1. SCREEN: 2.2.1-SCREEN.mp4

2.2.2. SCREEN: 2.2.2-SCREEN.mp4

2.2.3. SCREEN: 2.2.3-SCREEN.mp4: 00:01-00:08

2.3. Under **Test Type**, select the **Mann-Whitney U** test [1]. Click **OK** to run the test and allow SPSS to automatically generate the output [2].

2.3.1. SCREEN: 2.3.1-SCREEN.mp4: 00:01-00:05

2.3.2. SCREEN: 2.3.2-SCREEN.mp4: 00:00-00:09

2.4. For principal component analysis, ensure that the data is collated, saved in Excel or CSV format, and imported into SPSS version 20.0 [1]. To open the file, select **File**, then choose **Open**, followed by **Data**, and select the appropriate file [2].

2.4.1. SCREEN: 2.4.1-SCREEN.mp4: 00:00-00:05

2.4.2. SCREEN: 2.4.2-SCREEN.mp4: 00:00-00:17

2.5. To initiate Principal Component Analysis, click **Analyze**, then choose **Dimension Reduction**, and select **Factor [2-TXT]**.

2.5.1. SCREEN: 2.5.1-SCREEN.mp4 **TXT: Ensure missing values, outliers, and variable**

standardization are handled

- 2.6. In the dialog box, add all continuous variables used in Principal Component Analysis into the **Variables** field [1]. Click the **Extraction** button and select the **Principal Components** method as the extraction technique [2].

2.6.1. SCREEN: 2.6.1-SCREEN.mp4

2.6.2. SCREEN: 2.6.2-SCREEN.mp4.

- 2.7. Select Eigenvalues greater than 1 as the criterion for retaining principal components [1].

2.7.1. SCREEN: 2.7.1-SCREEN.mp4

- 2.8. Select the rotation method and click **Rotation** to choose either **Varimax** or **Promax** [1].

2.8.1. SCREEN: 2.8.1-SCREEN.mp4

- 2.9. Under Options, check both **Scree plot** and **Coefficient matrix** to include the gravel diagram and the matrix of coefficients in the output for evaluating retained variance [1]. After completing all the settings, click **OK** to execute the analysis and allow SPSS to generate the output [2].

2.9.1. SCREEN: 2.9.1-SCREEN.mp4

2.9.2. SCREEN: 2.9.2-SCREEN.mp4

- 2.10. Interpret the principal component loading matrix to assess the relationship between the principal components and the original variables [1]. Identify variables with higher loading values, as these contribute more significantly to component changes [2].

2.10.1. SCREEN: 2.10.1-SCREEN

2.10.2. SCREEN: 2.10.2-SCREEN: 00:17-00:20, 01:17-01:20

- 2.11. Use the **Total Variance Explained** table to evaluate how much variance each principal component accounts for [1]. Identify the principal components with large variance proportions, as they typically capture most of the data variation [2].

2.11.1. SCREEN: 2.11.1-SCREEN.mp4

2.11.2. SCREEN: 2.11.2-SCREEN.mp4: 00:00-00:08

2.12. Refer to the **scree plot** to determine which components to retain [1]. Locate the inflection point and keep all components to the left of this point [2].

2.12.1. SCREEN: 2.12.1-SCREEN.mp4

2.12.2. SCREEN: 2.12.2-SCREEN.mp4: 00:02-00:16

2.13. If principal component scores are required, check **Save as variables** before running the analysis [1]. SPSS will add the scores for each sample as new variables in the dataset [2].

2.13.1. SCREEN: 2.13.1-SCREEN.mp4

2.13.2. SCREEN: 2.13.2-SCREEN.mp4: 00:00-00:09

Results

3. Results

3.1. Principal component analysis identified 6 major components, which together accounted for 76.8% of the total variance [1]. The logistic regression model demonstrated stable performance across 3 validation folds, with AUC values of 0.71, 0.74, and 0.88, yielding a mean AUC of 0.77 [2].

3.1.1. LAB MEDIA: Figure 1.

3.1.2. LAB MEDIA: Figure 2. *Video editor: Highlight the individual ROC curves for folds 1, 2, and 3, showing their curve shapes and AUC values.*

3.2. In contrast, the random forest model exhibited greater variability, with fold AUC scores of 0.69, 0.52, and 0.83, and a lower mean AUC of 0.68 [1].

3.2.1. LAB MEDIA: Figure 3. *Video editor: Highlight the individual ROC curves for folds 1, 2, and 3, showing the inconsistent curve shapes and corresponding AUC values.*

3.3. The logistic regression model achieved 100% correct predictions for COPD and 6 out of 7 correct for respiratory tract infections, as shown in the confusion matrix, indicating high classification accuracy [1].

3.3.1. LAB MEDIA: Figure 4. *Video editor: Highlight the bottom-right cell showing 6 correct predictions for RTI.*

3.4. The random forest model misclassified 1 COPD and 2 respiratory tract infection cases, resulting in lower classification accuracy compared to the logistic regression model [1].

3.4.1. LAB MEDIA: Figure 5.

3.5. On the test dataset, the logistic regression model yielded excellent classification performance, achieving an AUC value of 0.95 [1]. The random forest model showed lower test performance with an AUC value of 0.76 [2].

3.5.1. LAB MEDIA: Figure 6. *Video editor: Highlight the orange ROC curve and the shaded region underneath it.*

3.5.2. LAB MEDIA: Figure 7. *Video editor: Highlight the orange ROC curve and the shaded region underneath it.*

1. Eigenvalue

Pronunciation link: <https://www.merriam-webster.com/dictionary/eigenvalue> ([Merriam-Webster](#))

IPA (American): /'aɪɡənˌvælju/ ([Wiktionary](#))

Phonetic spelling: EYE-gun-val-yoo

2. Mann-Whitney (as in Mann-Whitney U test)

Pronunciation link: <https://www.howtopronounce.com/mann-whitney> ([How To Pronounce](#))

IPA (American): /mæn'wɪtni/ ([How To Pronounce](#))

Phonetic spelling: man-WIT-nee

3. Principal Component Analysis

Pronunciation link: <https://www.collinsdictionary.com/dictionary/english/principal-component-analysis> ([Collins Dictionary](#))

IPA (American): /'prɪnsəpəl kəm'pəʊnənt ə'næləsɪs/ ([Collins Dictionary](#))

Phonetic spelling: PRIN-sə-pəl com-POH-nent uh-NAL-uh-sis

4. Variance

Pronunciation link: <https://dictionary.cambridge.org/pronunciation/english/variance> ([Cambridge Dictionary](#))

IPA (American): /'ver.i.əns/ ([Cambridge Dictionary](#))

Phonetic spelling: VAIR-ee-uhns

5. Rotation (in “rotation method”)

Pronunciation link: <https://www.merriam-webster.com/dictionary/rotation> ([Collins Dictionary](#)) (“rotation” appears in Collins and MW dictionaries; using “Collins” for “Eigenvalue” but “rotation” MW is standard)

IPA (American): /rəʊ'teɪʃən/ ([Collins Dictionary](#))

Phonetic spelling: roh-TAY-shun

6. Coefficient (in “coefficient matrix”)

Pronunciation link: <https://www.merriam-webster.com/dictionary/coefficient> ([Collins Dictionary](#))

IPA (American): /ˌkoʊə'fɪʃənt/ ([Collins Dictionary](#))

Phonetic spelling: koh-uh-FISH-ənt

7. **Scree** (as in “scree plot”)

Pronunciation link: <https://www.merriam-webster.com/dictionary/scree> ([Collins Dictionary](#))

IPA (American): /skri:/ ([Collins Dictionary](#))

Phonetic spelling: *skree*

8. **Confusion Matrix**

- *Confusion*

Pronunciation link: <https://www.merriam-webster.com/dictionary/confusion> ([Collins Dictionary](#))

IPA (American): /kən'fjuʒən/ ([Collins Dictionary](#))

Phonetic spelling: *kuhn-FYOOSH-uhn*

- *Matrix*

Pronunciation link: <https://www.merriam-webster.com/dictionary/matrix> ([Collins Dictionary](#))

IPA (American): /'meɪtrɪks/ ([Collins Dictionary](#))

Phonetic spelling: *MAY-triks*