# Wireless Earphone-Based Real-Time Monitoring of Breathing Exercises: A Deep Learning Approach

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46TH ANNUAL IEEE International Conference of the Engineering in Medicine and Biology Society
Orlando 2024
July 15-19, 2024

Poster No. 338

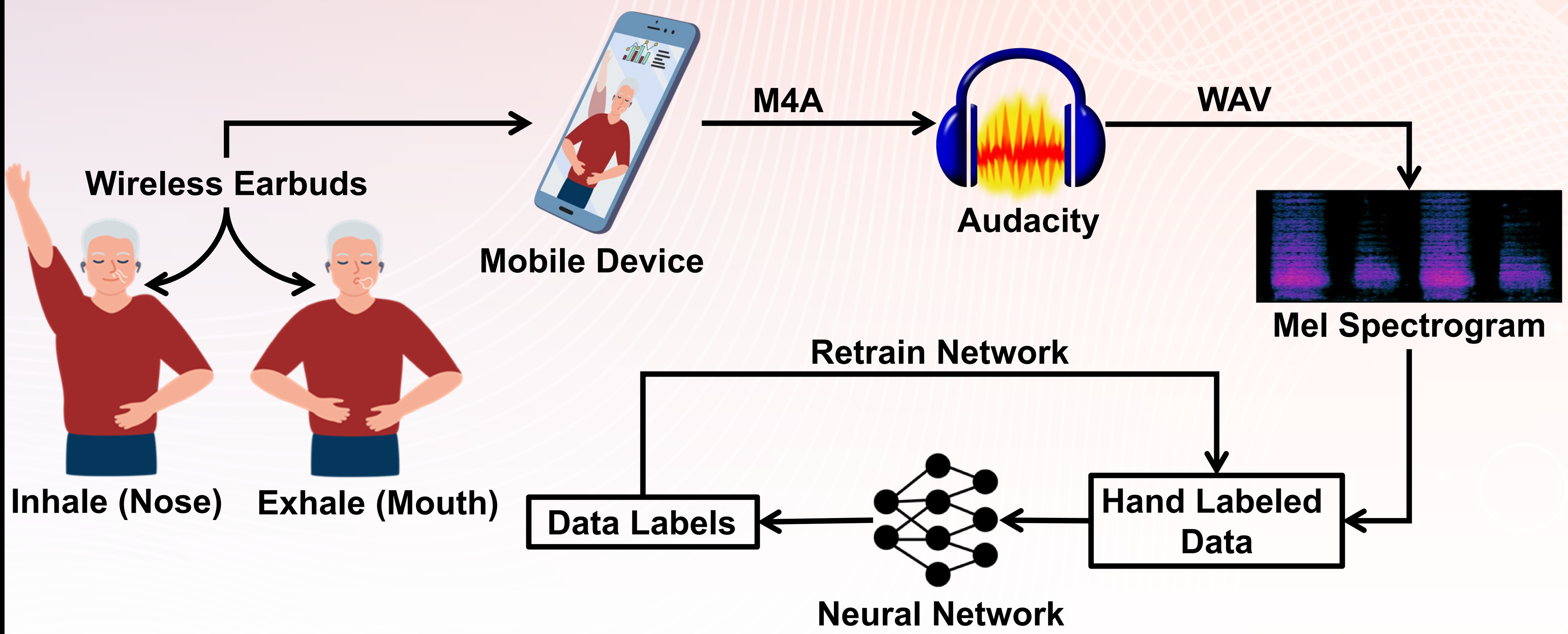
## INTRODUCTION

- **Deep breathing exercises** reduce **hypertension** and **anxiety**
- Used by several medical **therapy interventions**
  - **Lymphedema**, asthma, and chronic obstructive pulmonary disease
- **Tracking breathing** using a monitoring device **can support therapy compliance**
- **Lymphedema is an incurable condition** affecting 1 in 1000 Americans
  - Caused by an **obstruction in the lymphatic vessels**
  - Approximately **40% of breast cancer survivors suffer from lymphedema**
- **The optimal lymph flow (TOLF)**
  - Therapeutic **exercise program** for **post-operative breast cancer patients** to **prevent lymphedema**
  - Includes **easy-to-learn physical and breathing exercises**

**Proposal**

- Develop a system for **detection of breathing phases** (inhale/exhale) and **channels** (nose/mouth)
- Create an **annotated breathing audio dataset**, using wireless earphones

## DATA COLLECTION

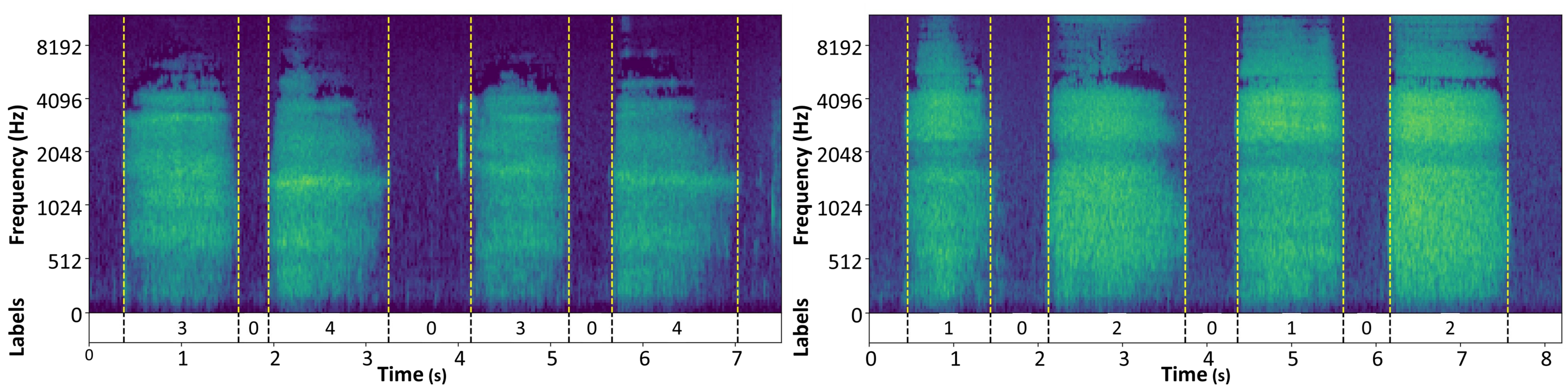



- **Eight healthy individuals performed controlled breathing exercises** (inhaling through the nose and exhaling through the mouth)
- **Breathing audio** was **captured using wireless earbuds** connected to a mobile device and the audio was **converted to WAV format**
- **Mel spectrograms** were generated to visualize the audio frequencies over time
- **Mel spectrograms of two audio files were manually labeled** to identify different parts of the breathing cycle (inhale and exhale phases)
- A binary **convolutional neural network** (CNN) was trained to **distinguish between pauses and breaths** and the pre-labeled files were manually corrected for minor mistakes
- The **CNN was iteratively retrained** with new audio data until it achieved **96% accuracy**

## TRAINING PIPELINE

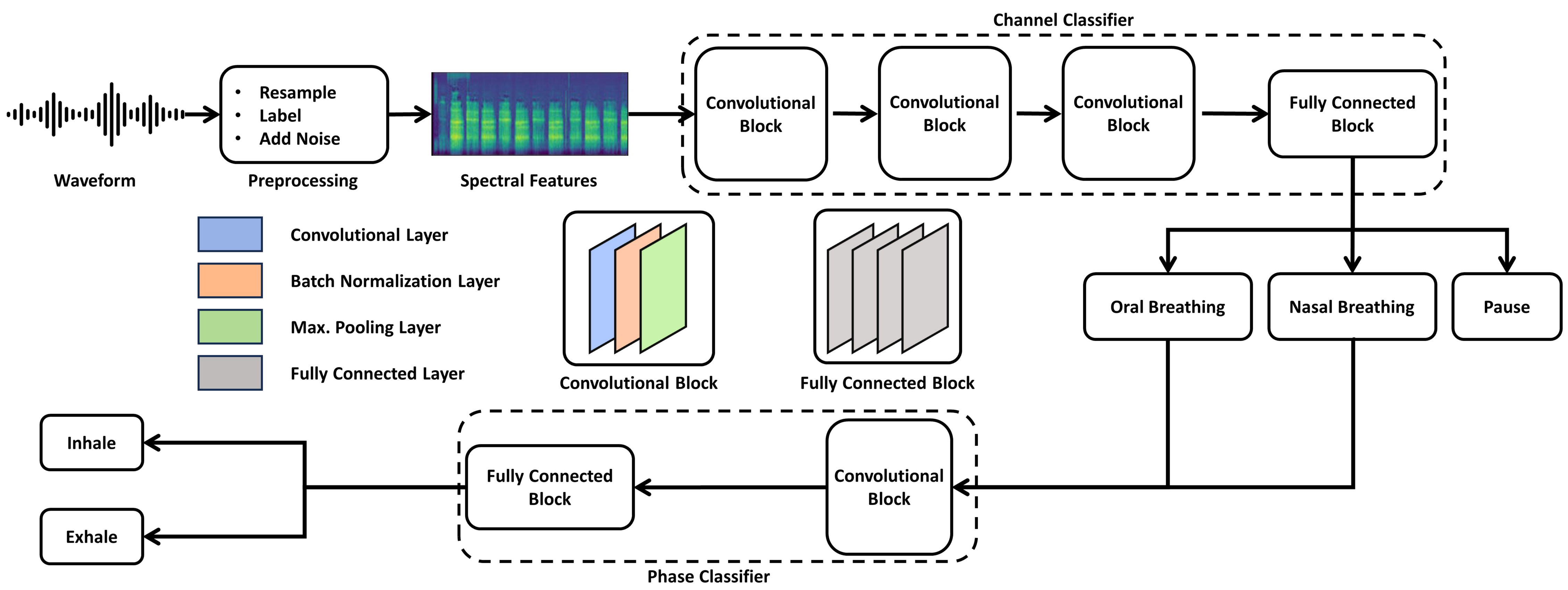
**Audio Preprocessing**

- **Resample audio** clips at 16 kHz
- **Segment and label audio** into 500 ms intervals with a 250 ms stride for overlap
- **Multilabeling** with **one-hot encoding**
- **Augmented training data with noise** (20 dB to 40 dB signal-to-noise ratio)
- **Convert** audio **to mel spectrograms** and **MFCCs**




**Model Training Pipeline**

- **Channel Classifier**
  - Three convolutional blocks each followed by batch normalization and max pooling
  - Four fully connected layers after the last convolutional block
  - **Classifies pause, nasal breathing, and oral breathing**
- **Phase Classifier**
  - Single convolutional block followed by four fully connected layers
  - **Distinguishes inhale from exhale** for nasal/oral segments
- Binary cross-entropy loss function used for training




## RESULTS

- **Leave-one-out cross-validation (LOOCV)** method was used with data from seven subjects for training and the eighth for validation
- **Channel Classifier**: Mel-spectrograms as input features yielded the best results with an average F1 score of 93.98% (SD=5.02%)
- **Phase Classifier**: Mel-spectrograms also outperformed MFCCs, with an average F1 score of 76.20% (SD=8.76%)
- Mel-spectrograms performed better than MFCCs for both channel and phase classification, although the phase classification scores were lower, indicating potential model or dataset limitations

| Classifier | Features | F1 Score (%) | | |
|---|---|---|---|---|
| | | Avg. (SD) | Max. | Min. |
| Channel | Mel spectrogram | 93.98 (5.02) | **97.99** | 82.45 |
| | MFCC | 90.35 (8.49) | 97.50 | 75.93 |
| Phase | Mel spectrogram | 76.20 (8.76) | **89.46** | 63.33 |
| | MFCC | 75.56 (8.55) | 87.35 | 63.71 |