

# Phonetic Analysis of Dysarthric Speech Tempo and Applications to Robust Personlised Dysarthric Speech Recognition

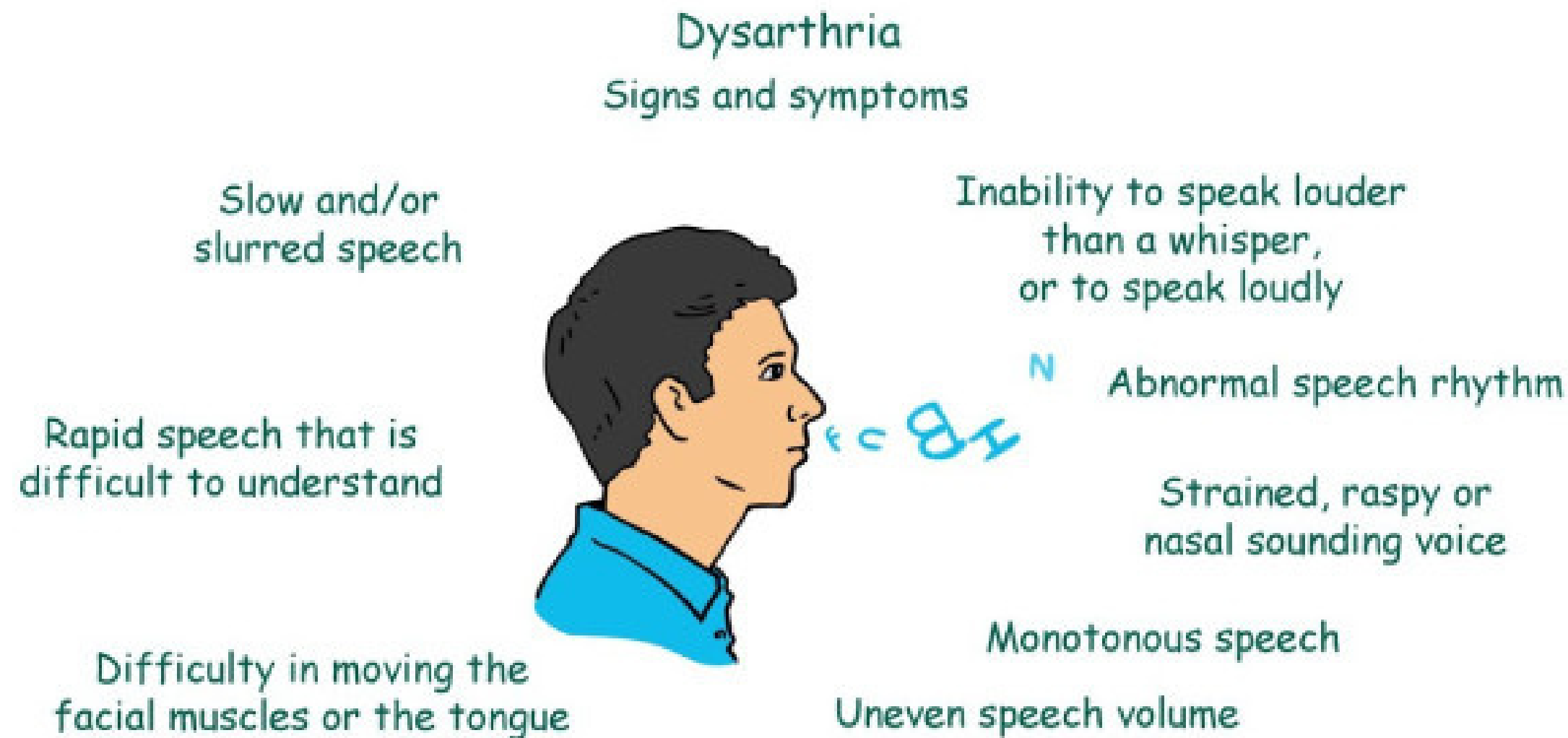
Feifei Xiong · Jon Barker · Heidi Christensen

IEEE ICASSP-2019

Saketh Reddy Vemula - 2022114014

Viswanath Vuppala - 2022101084

# Introduction



- Increased respiration frequency
- Inadequate Pauses
- Breathy or hoarse voice
- Reduced speech
- Deviations in pitch and volume
- Mis-articulated Sounds

# Why Phonemic Analysis?

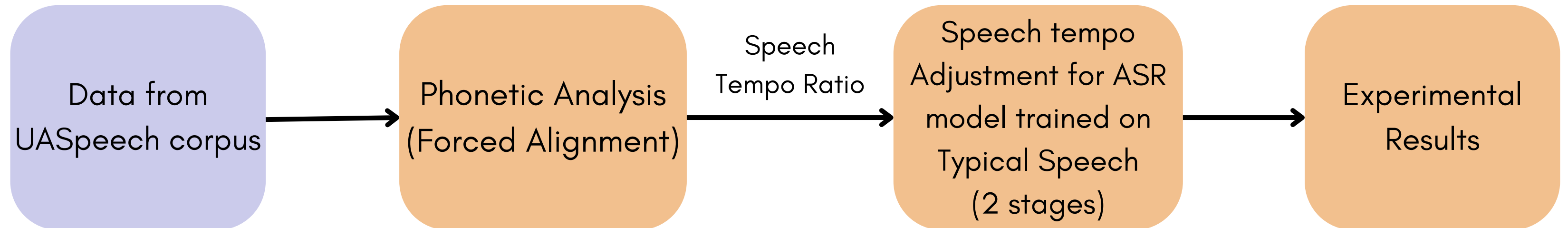
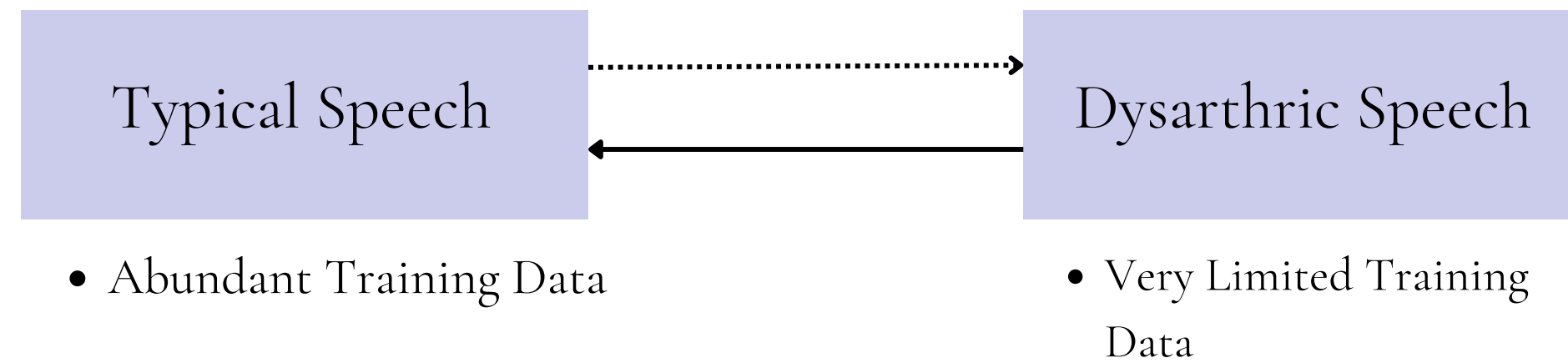
## Phonemes in Speech Recognition:

- Phonemes form the backbone of speech recognition systems by mapping acoustic signals to meaningful sounds (e.g., vowels and consonants).

## Challenges in Dysarthric Speech:

- Dysarthric speakers exhibit high phonemic variability, making it difficult for systems trained on typical speech to recognize dysarthric speech accurately.
- Dysarthria is **often associated with** severe physical disabilities like **Cerebral Palsy** (conditions that affect movement and posture).
- For this group of people, **speech-enabled and hands-free interfaces** often provide a more attractive and efficient means of access in comparison to hardwired switches, keyboards and remote controls.
- Hence, ASR is one of the best options to tackle this problem.

# Approach



# Phonetic Analysis

## Speech Tempo Analysis

- 1. Data Selection
- 2. Data Preprocessing
- 3. Forced-alignment
- 4. Speech Tempo Analysis based on Phoneme Segments

CTL: Control/Typical Speech  
DYS: Disorder/Dysarthric Speech

Training Data for STA

Sets(#Spk)	Re-segment	Block 1 & 3	Block 2	WER
CTL	✗	46410 (22.7 h)	23205 (11.1 h)	57.42
#13	✓	46403 (19.8 h)	23205 (9.7 h)	56.86
DYS	✗	49204 (44.3 h)	24731 (21.7 h)	48.60
#15	✓	49204 (27.3 h)	24727 (13.4 h)	44.91

WER: baseline ASR performance with DYS test set

Vowels #16	(V1) short vowels	AH AO AX EH IH UH
	(V2) medium vowels	AE
	(V3) long vowels	AA ER IY UW
	(V4) diphthongs	AW AY EY OW OY
Consonants #24	(C1) glides	L R W Y
	(C2) unvoiced stops	K P T
	(C3) voiced stops	B D G
	(C4) nasals	M N NG
	(C5) unvoiced fricatives	F S SH TH
	(C6) voiced fricatives	DH V Z ZH
	(C7) unvoiced affricates	CH
	(C8) voiced affricates	JH
	(C9) aspirates	HH

# Phonetic Analysis

## Speech Tempo Analysis

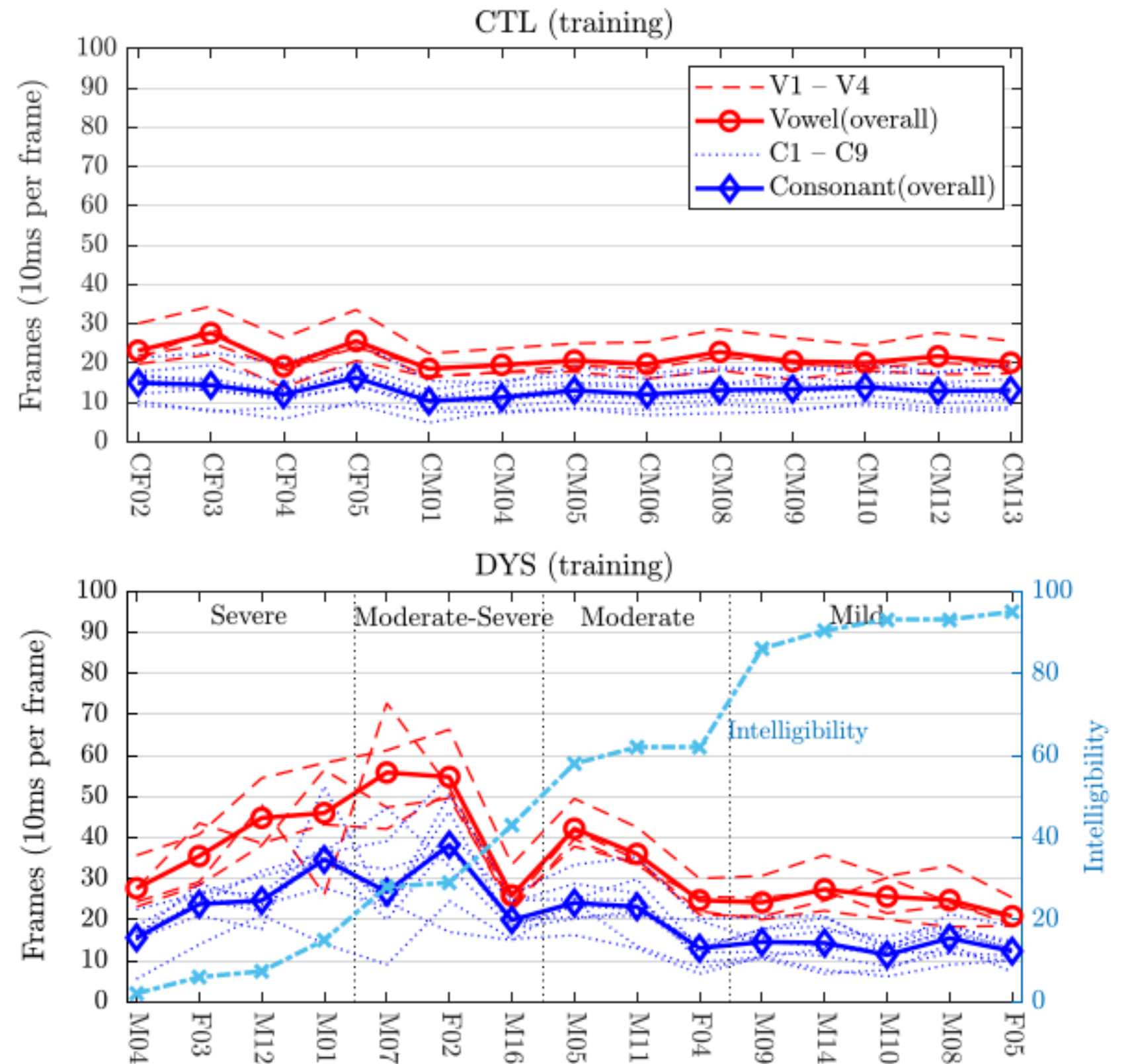
1. Data Selection
2. Data Preprocessing
3. Forced-alignment
4. Speech Tempo Analysis based on Phoneme Segments

Phoneme-based Speech Tempo Ratio:

$$\mathcal{R}_{d \leftarrow c}(p) = \frac{T_d(p)}{T_c(p)} \longrightarrow \overline{\mathcal{R}_{d \leftarrow c}}$$

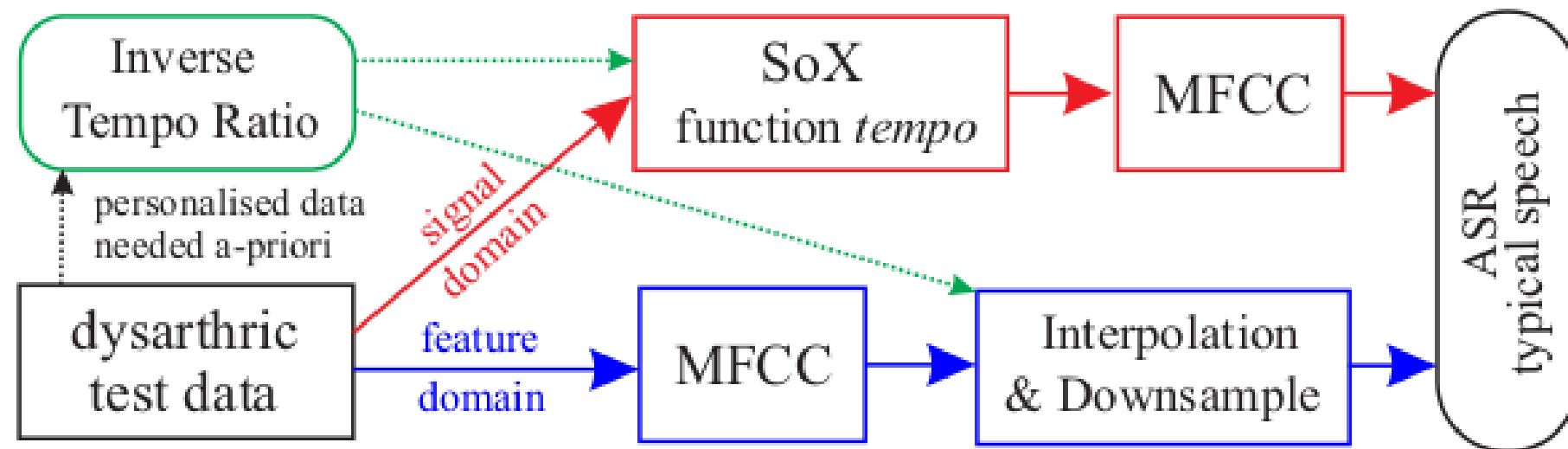
CTL: Control/Typical Speech

DYS: Disorder/Dysarthric Speech



# Speech Tempo Adjustment for ASR

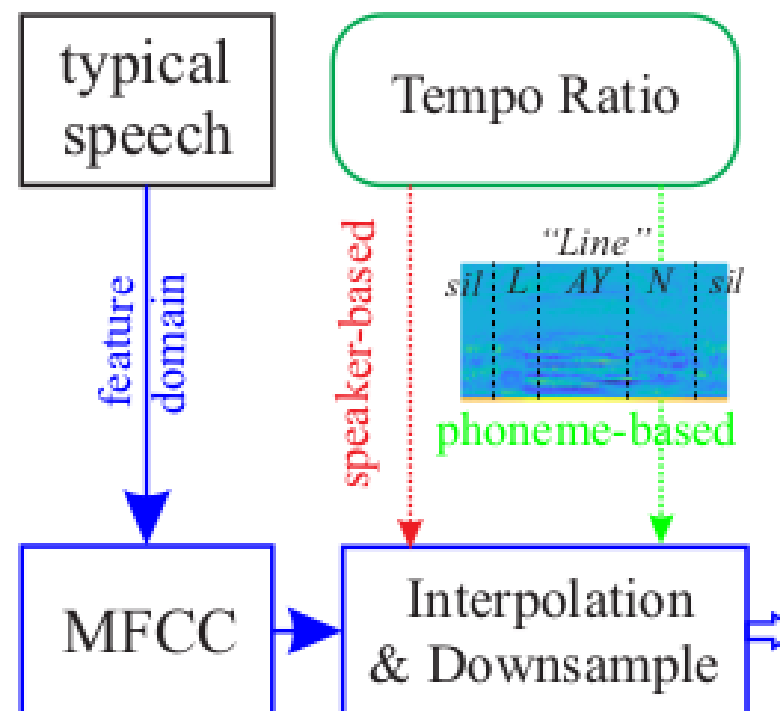
Test Stage  $\overline{\mathcal{R}_{d \leftarrow c}}$ :



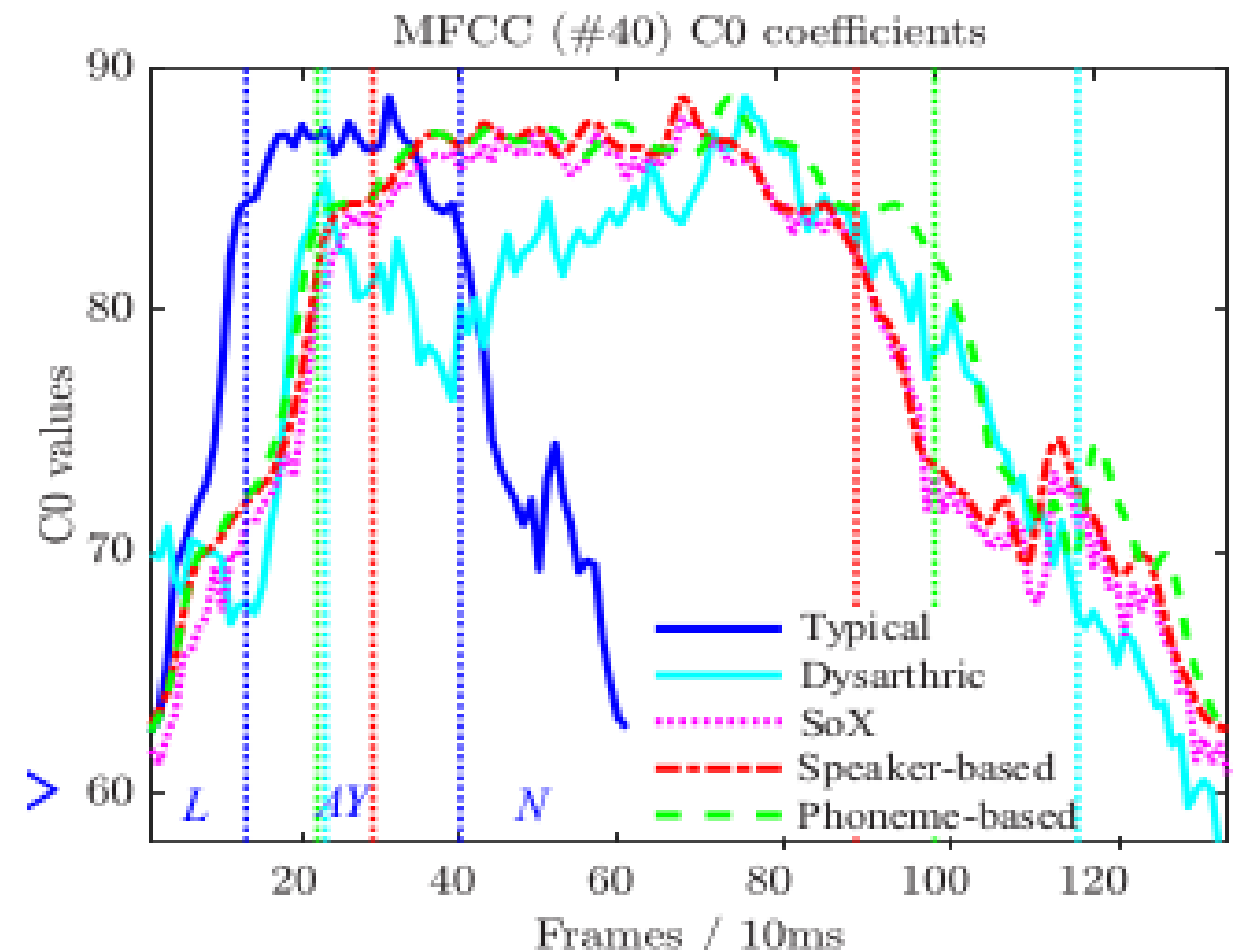
**Note:**

Phoneme-based tempo ratios are not possible in Test Stage due to lack of alignment knowledge in dysarthric test data

Training Stage



$$\mathcal{R}_{d \leftarrow c}(p) = \frac{T_d(p)}{T_c(p)}$$



# Experimental Results

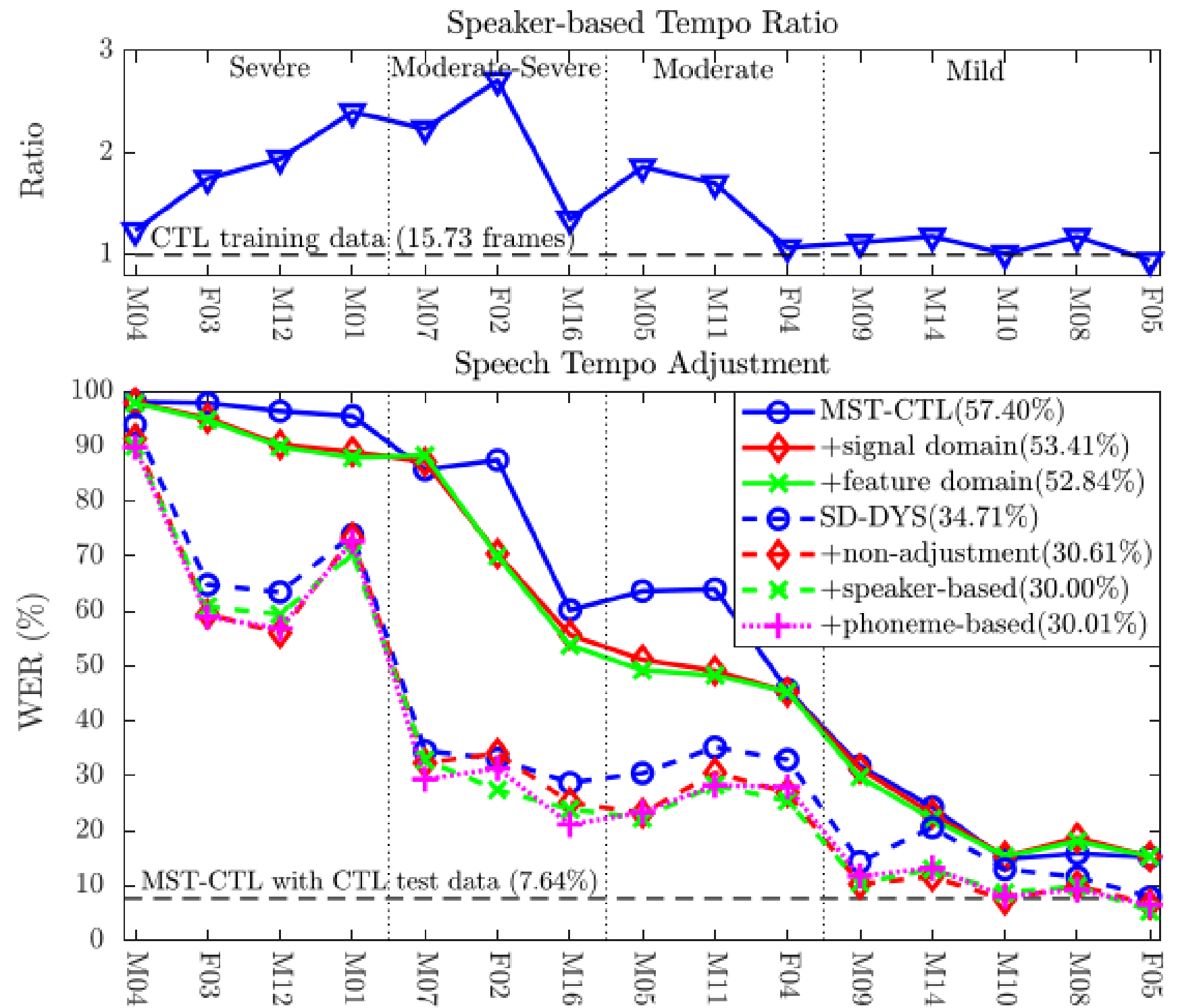
## WER vs Speech Tempo Adjustment methods

### Test Stage

1. Required to speed up withing 3 times to match
2. On Average, 4.6% absolute WER reduction can be achieved
3. Still far from SD-DYS

### Training Stage: Data Augmentation

Training	Severe	Mod.-Severe	Moderate	Mild	Overall
SD-DYS	72.65	32.25	32.70	13.44	34.71
+non-adjustment	68.22	30.74	26.66	<b>9.15</b>	30.61
+speaker-based	68.76	28.23	<b>25.13</b>	9.44	<b>30.00</b>
+V1–V4	69.33	29.13	25.47	9.62	30.50
+C1–C9	70.69	29.54	27.41	9.40	31.16
+phoneme-based	<b>67.83</b>	<b>27.55</b>	26.41	9.71	30.01

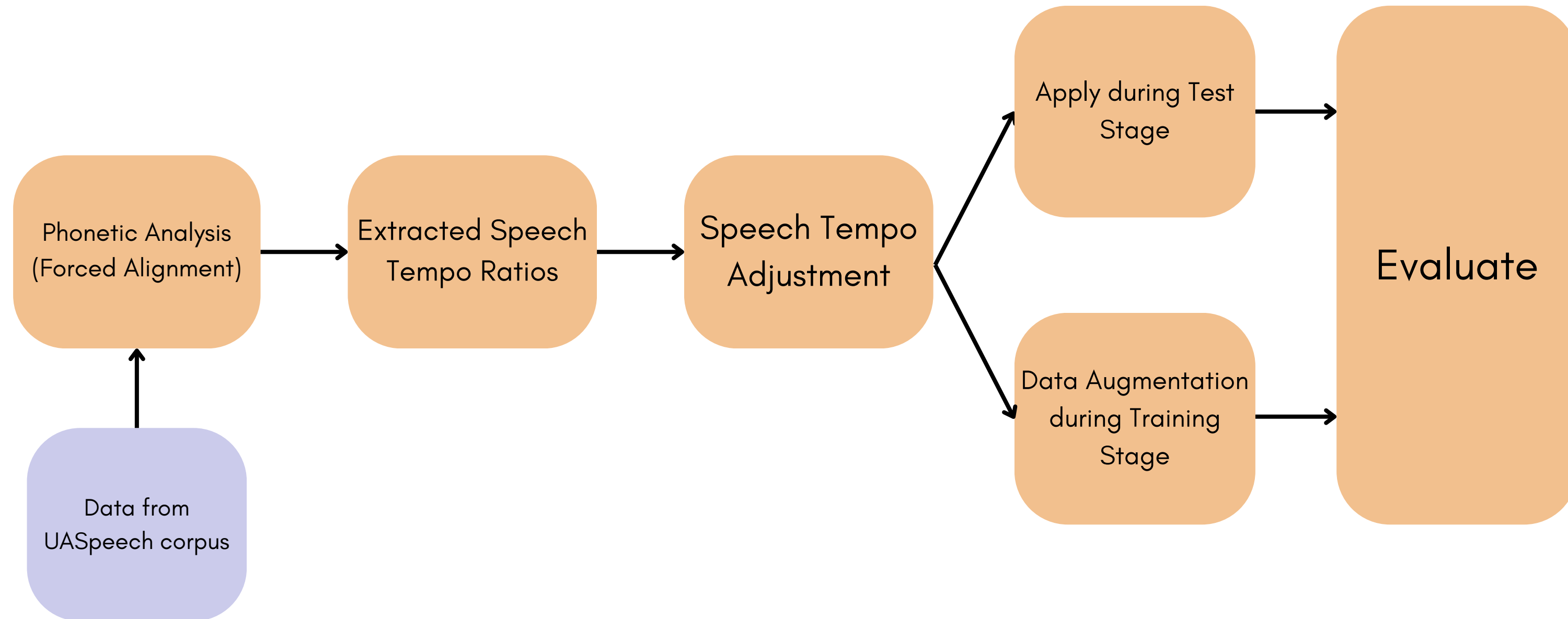




# Conclusion

Presents Two-approaches for improving Dysarthric Speech Recognition

Data Augmentation strategy is more effective with **7% absolute improvement** (after including more data 3x) in comparison to baseline speaker-depended trained system.





*Thank You*