# Speech task based automatic classification of ALS and Parkinson's Disease and their severity using log Mel spectrograms

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# Overview



#### 1 Introduction

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#### 5 Conclusions

# Amyotrophic Lateral Sclerosis (ALS)



- A motor neuron disorder
- Neurons : communication link
- Gradual degeneration of motor neurons
- Loss of muscle control



Morris, Jerry. "Amyotrophic lateral sclerosis (ALS) and related motor neuron diseases: an overview." The Neurodiagnostic Journal 55.3 (2015): 180-194.

# Symptoms of ALS



- Muscle stiffness
- A hard time in holding items
- Muscle cramps
- Swallowing problems
- Speech difficulties (slurred or slowness)

 $\label{eq:Mayo} Mayo Clinic, 'Amyotrophic Lateral Sclerosis - Symptoms and causes', 6 August 2019. [Online]. Available:$  $https://www.mayoclinic.org/diseases-conditions/amyotrophic-lateral-sclerosis/symptoms-causes/syc-20354022 <math display="inline">\equiv *$ 

# Parkinson's Disease (PD)

A progressive brain disorder

- Impairment of nerve cells
- Neurons : Dopamine production
- Movement issues





<sup>&</sup>quot;Parkinson's Disease." National Institute on Aging, U.S. Department of Health and Human Services, May 2017. [Online]. Available: www.nia.nih.gov/health/parkinsons-disease.

# Symptoms of PD



- Tremors (hands, arms, legs)
- Stiffness in limbs and trunk
- Slowness in movements
- Difficulty in swallowing and chewing
- Speech difficulties (slurred or slowness)

Mayo Clinic, 'Parkinson's disease - Symptoms and causes', 30 June 2018. [Online]. Available: https://www.mayoclinic.org/diseases-conditions/parkinsons-disease/symptoms-causes/syc-20376055 < = > < < = >

# Life expectancy with ALS or PD



- ALS affected people<sup>1,2</sup>
  - 50% people 3 or more years
  - 20% people 5 or more years
  - 10% people 10 or more years
- PD affected people<sup>3</sup>
  - Has increased from 9.4 (1967) to 14.6 years (2016) after diagnosis

1. C. Arthur, et al., "Projected increase in Amyotrophic Lateral Sclerosis from 2015 to 2040," Nature communications, vol. 7, p. 12408, 2016

2. A. Nalini, et al., "Clinical characteristics and survival pattern of 1153 patientswith Amyotrophic Lateral Sclerosis: experience over 30 years fromIndia," Journal of the Neurological Sciences, vol. 272, no. 1-2, pp. 60–70, 2008.

3. Golbe, Lawrence I., and Cristian E. Leyton. "Life expectancy in Parkinson disease." (2018): 991=992. 🗐 👘 👰 🛷

# Diagnosis and Treatment for ALS and PD



- Currently no specific tests that can confirm of having ALS or PD  $^1$
- Diagnosis
- No cure for either ALS or PD although there exists some treatment for managing their symptoms <sup>1,2,3</sup>

- 1. Veritas Neuro, "ALS vs Parkinson's How Do These Conditions Differ?" Aug 2019. [Online]. Available: https://alstreatment.com/als-vs-parkinsons/
  - 2. A. N. Lieberman, "Update on Parkinson disease." New York State Journal of Medicine, 1987.
  - 3. J.-P. Julien, "ALS: Astrocytes move in as deadly neighbors," Nature Neuroscience, vol. 10, no. 5, pp. 535–537, 2007 🔍 🔿

# Motivation, Plans and Challenges



#### Motivation

- Objective : Automated methods
- What's new? : Methodology + Severity classification
- Future Plan: Supplementing diagnosis

#### Challenges

- Identifying speech cues
- Access for people of different socio-economic backgrounds

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Data collection



# Speech waveforms and spectograms of ALS, PD, and Healthy controls



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# Literature Survey



- Performance of various speech tasks in automatic classification between ALS and HC using SVM and DNN<sup>1</sup>. As seen, the spectro-temporal characteristics change depending on ALS/HC (and similarly for PD)
- CNNs for identifying ALS patients<sup>2</sup> using two 1-D convolution networks - (one each for time and frequency respectively) for filter bank features (MFBE)

<sup>1.</sup> Suhas B.N., "Comparison of Speech Tasks and Recording Devices for Voice Based Automatic Classification of Healthy Subjects and Patients with Amyotrophic Lateral Sclerosis," inProc. Interspeech 2019, 2019, pp. 4564–4568.

<sup>2.</sup> An, KwangHoon, et al. "Automatic Early Detection of Amyotrophic Lateral Sclerosis from Intelligible Speech Using Convolutional Neural Networks." Interspeech. 2018.

# SPIRE LAB

# Goal of this work

- Performance of log Mel Spectrograms in 3 class ALS/PD/HC, 5 class ALS/3 class PD severity detection
- Propose a 2D CNN approach that incorporates both Time-Frequency (TF) plane which helps us to model temporal and harmonic structures of audio signals

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# 2D CNN and Feature dimensions



- The work makes use of TF plane as a whole and utilizes a 2-dimensional convolutional network for log Mel spectrograms (SPEC) and Mel frequency cepstral coefficients (MFCC)
- Due to the TF plane, the feature is better understood through a 2D CNN (finer modelling of temporal-harmonic structures)
- **I** SPEC dimension of  $96 \times 33$  with Melbins<sup>1</sup> = 96, and a audio length of 1 second represented by 33 frames
- 2 MFCC dimension of  $101\times 39$  with audio length represented by 101 frames and feature dimension of 39

# 2D CNN Architecture





- No. conv. filters or 'feature maps' = 32
- Kernel : A 3 × 3 (represented by 2D Conv)
- Convolution layer of size  $(h \times w \times d)$  learns ' d ' features of size  $h \times w$ .
- Size of pooling area :  $2 \times 2$  (represented by Max Pool 2)

# 2D CNN architecture (contd.)





- Activation function : ReLU (softmax @ output)
- $\blacksquare$  Optimum conv. layer dropout is =0.5 ; dense layer dropout =0.6
- Loss function : Categorical cross-entropy
- Optimizer : Adadelta

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# Data collection



- Collected from National Institute of Mental Health and Neurosciences (NIMHANS), Bengaluru, India
- Recorders : Apple iPhone 7 (IPH), Motorola G5 Plus (MOT), Xiaomi Redmi 4 (XIA), Zoom H6 X/Y recorder (ZOO) and Dell XPS 15 laptop (LAP)
- Sampling frequency : 44.1 kHz

#### Dataset



#### Number of subjects used in this work:

- 60 ALS (30 Male, 30 Female)
- 60 PD (34 Male, 26 Female)
- 60 healthy control (HC) (30 Male, 30 Female)

Condition	Condition Gender Count		Age Range (Avg) in years		
ALS	М	30	33 - 76 (58.60)		
	F	30	38 - 75 (56.02)		
PD	М	34	34 - 78 (58.22)		
	F	26	36 - 74 (56.99)		
НС	М	30	26 - 68 (44.21)		
	F	30	31 - 65 (46.93)		

Table: Subject count and age range for each condition - gender pair

#### Dataset



#### Number of subjects used in this work:

- 60 ALS (30 Male, 30 Female)
- 60 PD (34 Male, 26 Female)
- 60 healthy control (HC) (30 Male, 30 Female)

#### Speech tasks: considering all subjects across all devices

- Spontaneous speech (SPON) 21 hours
- Diadochokinetic rate (DIDK) 22.42 hours
- Sustained phoneme production (PHON) 25.84 hours
- Image Description (IMAG) 25.22 hours

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# Severity Ratings



- Provided by five speech language pathologists (SLP) from NIMHANS
- Inter-rater reliability <sup>1</sup> has been calculated using the Fleiss' kappa (κ)
  - ALS subjects, κ = 0.9017 (Almost perfect agreement)
  - PD subjects, κ = 0.6995 (Substantial agreement)

ALSFRS-R for Speech	UPDRS-III for Speech		
Finding		Finding	Sev
Normal	4	Normal	0
Detectable speech disturbance	3	Slight loss of expression, diction and/or volume.	1
Intelligible with repeating	2	Monotone, slurred but understandable; moderately impaired.	2
Speech combined with nonvocal communications	1	Marked impairment, difficult to understand.	3
Loss of useful speech	0	Unintelligible.	4

Table: ALSFRS-R (for ALS) and UPDRS-III (for PD) scales used for rating the subjects

<sup>1.</sup> Zapf, A., Castell, S., Morawietz, L. et al. Measuring inter-rater reliability for nominal data – which coefficients and confidence intervals are appropriate?. BMC Med Res Methodol 16, 93 (2016). https://doi.org/10.1186/s12874=016-0200-9 🔿 <

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# Experimental setup



- 5 fold cross validation (each fold consists of 12 ALS, 12 PD, 12 HC)
- Proposed approach: 2D CNN : Uses ReLU activation function (except for softmax before output)
  - Features: SPEC and MFCC (computed for window length of 20ms & shift of 10ms, analysis window of 1s).
- Baseline: SVM and DNN for ALS/PD/HC
  - Features: MFCC (suprasegmental features on 1s analysis window)
  - Kernel function in SVM: Radial basis function
  - DNN: 2-hidden layers with 128/256/512 units in each layer (for which the val. loss is minimized) and output layer with three units (ALS/PD/HC) and softmax activation

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Figure: AUC-ROC curves for 2 class classification with True Positive Rate (TPR) vs False Positive Rate (FPR) on the Y & X axis

 $\uparrow$  AUC  $\Leftrightarrow$  better ability of the the model at distinguishing between classes.

<sup>1.</sup> S. Narkhede, "Understanding AUC - ROC Curve," May 2019. [Online]. Available: https://towardsdatascience.com/ understanding-auc-roc-curve-68b2303cc9c5





Three sets of classification experiments are carried out:

- **1** 3 class ALS vs PD vs HC
- 2 5 class ALS severity classification
- **3** class PD severity classification



# 3 class ALS vs PD vs HC

Speech	Task/Device	МОТ	Z00	IPH	XIA	LAP
SPON	SPEC	0.86	0.85	0.85	0.84	0.84
		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
	MECC	0.67	0.68	0.67	0.68	0.64
	IVIFCC	(0.04)	(0.04)	(0.08)	(0.03)	(0.01)
	SDEC	0.93	0.90	0.92	0.90	0.89
DIDK	SPEC	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
	MFCC	0.74	0.72	0.73	0.73	0.75
		(0.04)	(0.05)	(0.06)	(0.01)	(0.03)
	SDEC	0.89	0.80	0.86	0.80	0.83
PHON	SFEC	(0.0)	(0.01)	(0.01)	(0.01)	(0.01)
	MECC	0.72	0.70	0.70	0.68	0.67
	IVIFCC	(0.04)	(0.05)	(0.05)	(0.02)	(0.07)
IMAG	SPEC	0.84	0.82	0.86	0.80	0.81
		(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
	MFCC	0.72	0.77	0.75	0.66	0.72
		(0.01)	(0.04)	(0.03)	(0.03)	(0.01)

Table: Comparison of accuracy (with SD in brackets) across 5 folds for different tasks and devices between MFCC baseline and SPEC

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# AUC-ROC for 3 class ALS/PD/HC





- Tasks (columns) & devices (rows) with TPR vs FPR on the Y & X axis
- Bold lines : SPEC
  Dashed lines : MFCC.
- AUC scores for MFCC are in brackets next to the SPEC values for reference

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# Experiments



Three sets of classification experiments are carried out:

- 1 3 class ALS vs PD vs HC
- **2** 5 class ALS severity classification
- **3** class PD severity classification



# 5 class ALS severity classification

Speech	Task/Device	MOT	Z00	IPH	XIA	LAP
SPON	SPEC	0.76	0.73	0.80	0.74	0.74
		(0.08)	(0.09)	(0.09)	(0.04)	(0.06)
	MFCC	0.70	0.62	0.72	0.61	0.66
		(0.09)	(0.01)	(0.01)	(0.05)	(0.07)
	SPEC	0.74	0.77	0.79	0.78	0.76
DIDK		(0.01)	(0.07)	(0.01)	(0.01)	(0.01)
	MFCC	0.64	0.67	0.70	0.65	0.65
		(0.01)	(0.08)	(0.01)	(0.01)	(0.02)
	SPEC	0.70	0.68	0.72	0.71	0.70
PHON		(0.07)	(0.01)	(0.01)	(0.08)	(0.08)
	MECC	0.64	0.55	0.65	0.60	0.58
	WITCC	(0.08)	(0.01)	(0.01)	(0.09)	(0.09)
	SPEC	0.77	0.75	0.74	0.74	0.74
IMAG		(0.05)	(0.06)	(0.07)	(0.08)	(0.01)
	MFCC	0.67	0.66	0.72	0.70	0.68
		(0.06)	(0.08)	(0.08)	(0.09)	(0.02)

Table: Comparison of accuracy (with SD in brackets) across 5 folds for different tasks and devices between SPEC and MFCC for 5 class ALS Severity classification



# AUC-ROC for 5 class ALS Severity





Tasks (columns) & devices (rows) with TPR vs FPR on the Y & X axis <u>Severity</u>: 0 : Severe (loss of useful speech) and 4 : Normal speech (but has ALS)

# Experiments



Three sets of classification experiments are carried out:

- 1 3 class ALS vs PD vs HC
- 2 5 class ALS severity classification
- **3** class PD severity classification



# 3 class PD severity classification

Speech	Task/Device	мот	Z00	IPH	XIA	LAP
	SPEC	0.75	0.76	0.76	0.76	0.77
SPON		(0.01)	(0.01)	(0.01)	(0.01)	(0.06)
	MFCC	0.65	0.68	0.69	0.63	0.61
		(0.04)	(0.01)	(0.03)	(0.01)	(0.01)
	CDEC	0.87	0.87	0.85	0.85	0.86
DIDK	SFEC	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
	MFCC	0.80	0.82	0.84	0.80	0.79
		(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
	SPEC	0.85	0.81	0.82	0.79	0.77
PHON		(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
	MECC	0.68	0.75	0.62	0.66	0.70
	ivii ee	(0.04)	(0.05)	(0.08)	(0.09)	(0.01)
	SPEC	0.81	0.79	0.81	0.76	0.77
IMAG		(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
	MFCC	0.70	0.74	0.75	0.70	0.67
		(0.05)	(0.04)	(0.02)	(0.01)	(0.03)

Table: Comparison of accuracy (with SD in brackets) across 5 folds for different tasks and devices between SPEC and MFCC for 3 class PD Severity classification

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# AUC-ROC for 3 class PD Severity





Tasks (columns) & devices (rows) with TPR vs FPR on the Y & X axis Severity:

- 0: Normal speech (but has PD)
- 2: Monotone, slurred but understandable; moderately impaired

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# Summary



- 2D CNN+SPEC outperforms 2D CNN+MFCC across all speech task-device pairs
- 2D CNN+MFCC in turn performs better than SVM+MFCC or DNN+MFCC for ALS/PD/HC classification
- 5 class ALS Severity : Across all severity-speech task-device combinations, the max(min) AUC score is 0.976(0.866) - good separability between severity classes
- 3 class PD Severity : Across all severity-speech task-device combinations, the max(min) AUC score is 0.951(0.807) - (which may further improve with an increase in Fleiss' kappa (κ))

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# Key Takeaways

- SPEC features performed better than MFCC and regardless of the recording device used, similar accuracies were obtained
- Severity classification (to the best of our knowledge) of a neurological disease such as ALS or PD having not been attempted earlier shows good promise in identifying the condition and also its severity at an earlier stage

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#### THANK YOU

#### Have Questions/Suggestions? Write to us at spirelab.ee@iisc.ac.in

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