Voice based classification of patients with Amyotrophic Lateral Sclerosis, Parkinson's Disease and Healthy Controls with CNN-LSTM using transfer learning

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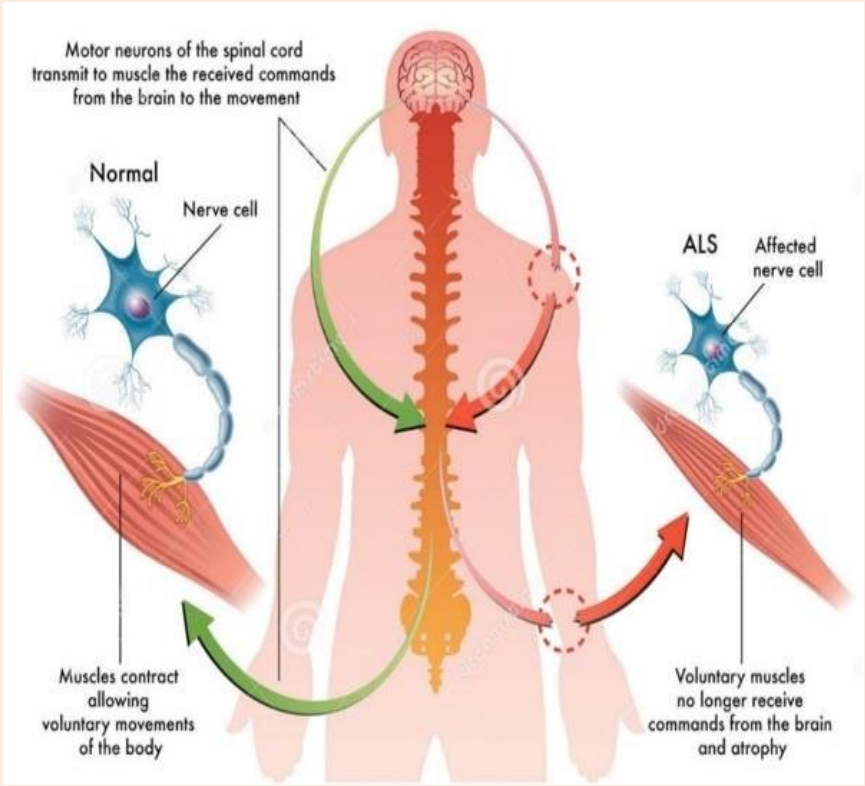
Poster Session: TU2.PB.11:Speech Analysis and Coding
Tuesday, 5 May, 2020, 16:30-18:30

Overview

Amyotrophic Lateral Sclerosis (ALS)

- A progressive motor neuron disease
- Affects nerve cells in the brain and spinal cord
- Results in loss of muscle control.



The ALS Association,"What is ALS?", May 2019.

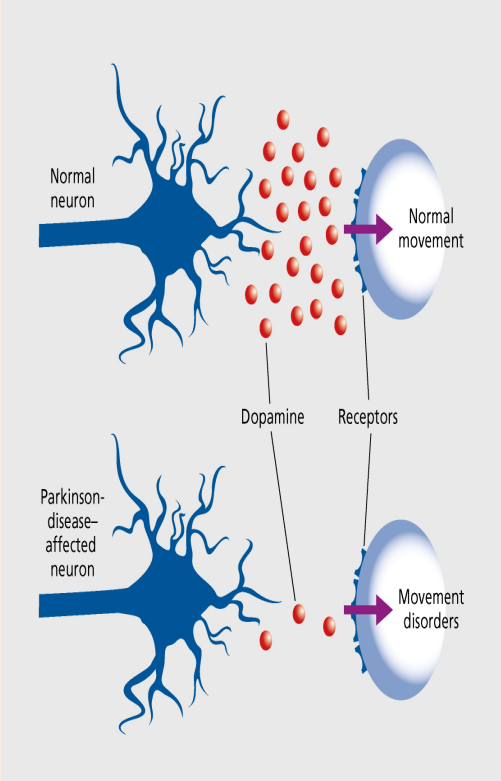
Symptoms of ALS

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

Mayo Clinic, 'Amyotrophic Lateral Sclerosis - Symptoms and causes', 6 August 2019

Parkinson's Disease (PD)

- A progressive brain disorder
- Occurs when nerve cells in brain gets damaged
- Reduces the DOPAMINE level in brain
- Results in movement problems.



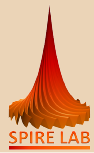
Parkinson's Foundation, "What is Parkinson's? "

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

Life expectancy with ALS or PD



- ALS affected people[1]
  - 50% people - 3 or more years
  - 20% people - 5 or more years
  - 10% people - 10 or more years
- PD affected people[2]
  - 10 to 20 years after being diagnosed

1. The ALS Association,Facts you should know, May 2019.
2. Life expectancy in Parkinson disease Lawrence I. Golbe, Cristian E. Leyton Neurology Nov 2018, 91 (22) 991-992.

Diagnosis for ALS and PD

- Currently no specific tests that can confirm of having ALS or PD
- Diagnosis is based on medical history (11 months) and a neurological examination

The ALS Association,Symptoms and Diagnosis, May 2019.

Treatment for ALS and PD

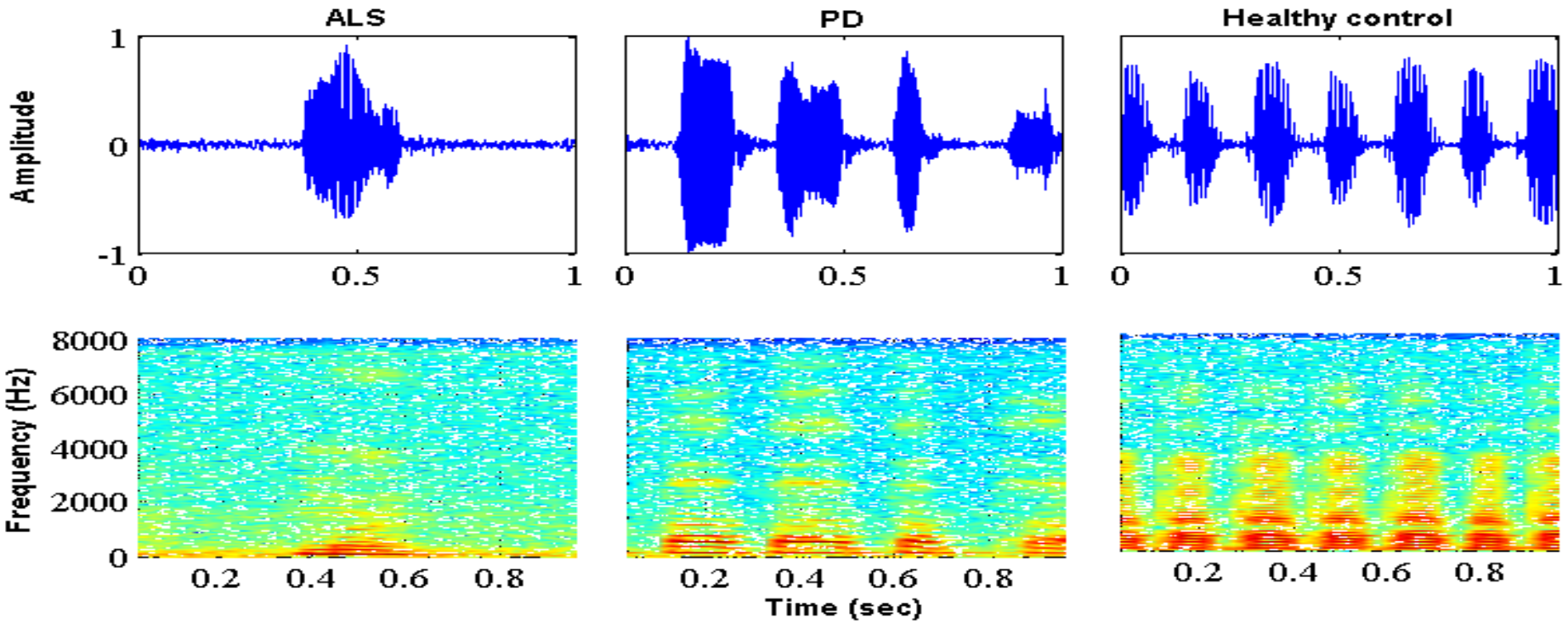
- Currently NO cure for ALS and PD
- Early detection can help to prolong survival and quality of life

The ALS Association,Facts you should know, May 2019.

Motivation

- Automated methods for detection of ALS or PD could reduce diagnosis time
- To develop a mobile application that helps in early detection and to follow the progression of the disease using speech as a biomarker

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



Literature Survey

- From diadochokinetic rate, using syllable rate and maximum phonation duration, automatic classification of ALS patients has been attempted based on fractal analysis

Antje S Mefferd, "Speaking rate effects on articulatory pattern consistency in talkers with mild ALS, "Clinical linguistics & phonetics, vol. 28, no.11, pp. 799–811, 2014.

Literature Survey

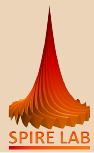
- Studied the performance of three different speech tasks namely, Spontaneous speech (SPON), Diadochokinetic rate (DIDK), and Sustained phoneme production (PHON) in automatic classification between ALS and Healthy Control (HC) using SVM and DNN

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.

Challenges

- Data collection from ALS and PD patients is often tedious making a large corpus development a challenging task
- Automated methods require huge amount of data to train a classifier

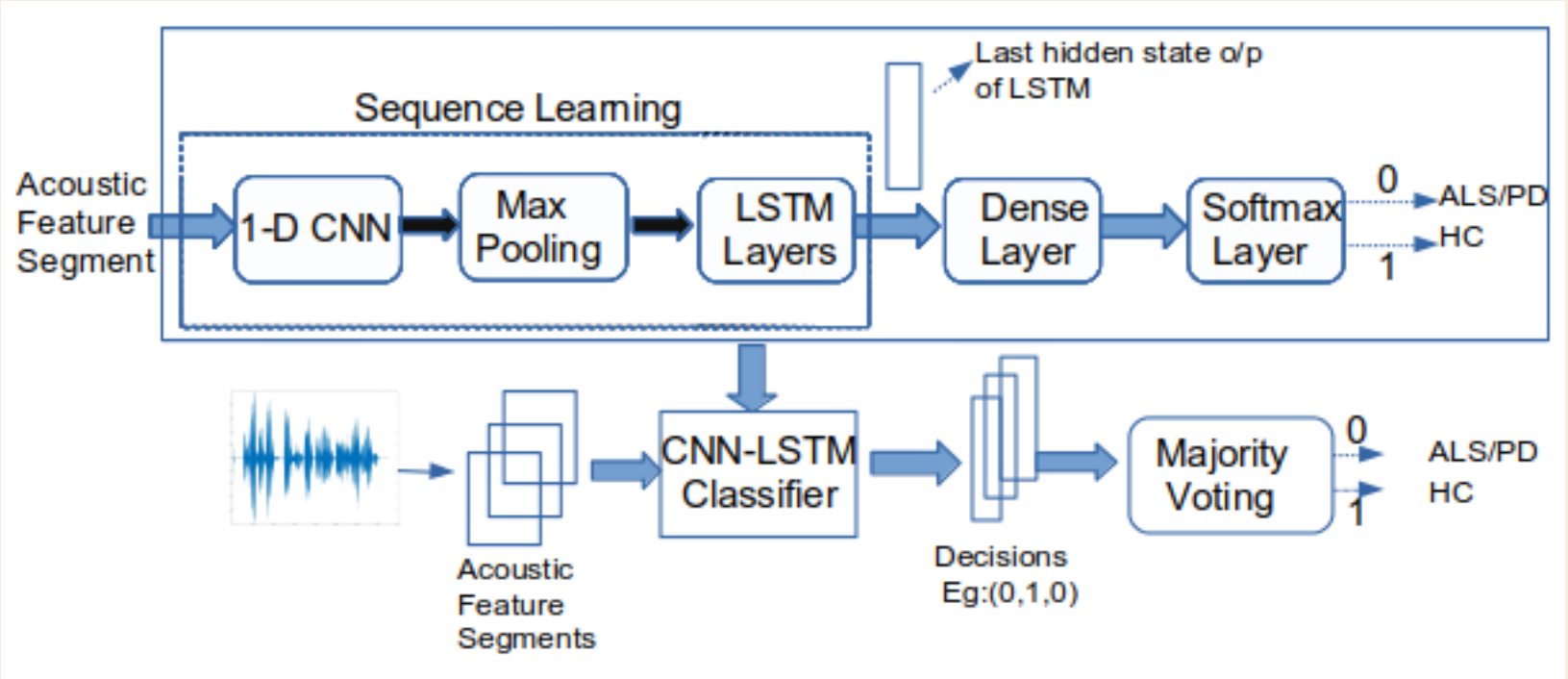
Goal of this work



- To study the performance of the classifier in low resource condition and benefit of Transfer Learning in such scenarios
- Also we are proposing CNN-LSTM approach and comparing with the existing DNN and SVM approaches

Overview

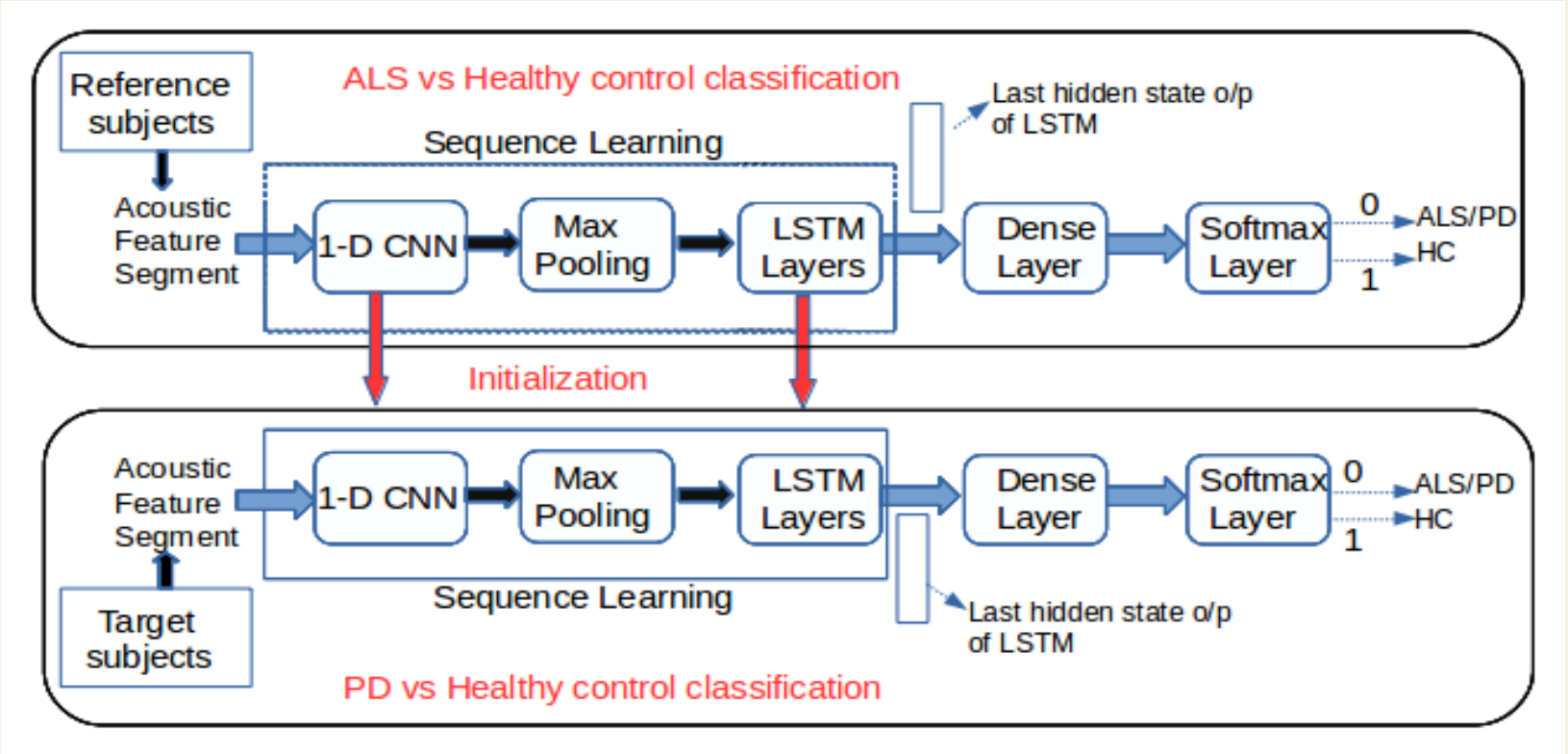
CNN-LSTM


Sequence Learning
Last hidden state o/p of LSTM
Acoustic Feature Segment
1-D CNN
Max Pooling
LSTM Layers
Dense Layer
Softmax Layer
0
1
ALS/PD
HC
CNN-LSTM Classifier
Acoustic Feature Segments
Decisions Eg:(0,1,0)
Majority Voting
0
1
ALS/PD
HC

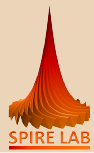
Transfer Learning

- Machine learning approach where weights of a neural network model trained for a particular task are utilized as the initialization of weights for a model with a different task.
- Useful during unavailability of large amounts of training data

CNN-LSTM using transfer learning



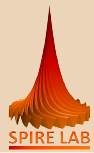
Objectives of the experiments



- Comparing the performance of CNN-LSTM to ALS classification with those of baseline schemes based on SVM and DNN.
- Transfer learning approach for 2-class classifications (ALS/HC;PD/HC) in low resource data condition
- 3-class classification(ALS/PD/HC) with CNN-LSTM

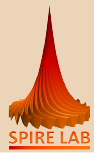
Overview

Data collection



- Collected from National Institute of Mental Health and Neurosciences (NIMHANS), Bengaluru, India.
- Recorder : Zoom H-6 recorder with XYH-6 X/Y capsule high quality unidirectional microphone.
- Sampling frequency : 44.1 kHz

Dataset



- Number of subjects used in this work:
  - 60 ALS (30 Male, 30 Female)
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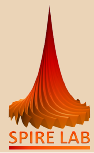
Dataset



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  - Spontaneous speech (SPON) - 5.62 hours
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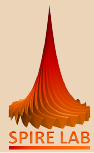
  - Diadochokinetic rate (DIDK) - 4.65 hours

Overview

Experimental setup



- 5 fold cross validation (each fold consists of 12 ALS, 12 PD, 12 HC)
- Proposed approach: CNN-LSTM
  - Features: Mel frequency cepstral coefficients (MFCC) with window length (20ms) and shift (10ms).
- Baseline: SVM and DNN for ALS/HC
  - Features: MFCC (suprasegmental features on 2sec analysis window)
  - Kernel function in SVM: Radial basis function
  - DNN: 2-hidden layers with 128 units in each layer and output layer with two units and softmax activation.

Objectives of the experiments

- **Comparing the performance of CNN-LSTM to ALS classification with those of baseline schemes based on SVM and DNN**.
- Transfer learning approach for 2-class classifications (ALS/HC;PD/HC) in low resource data condition
- 3-class classification(ALS/PD/HC) with CNN-LSTM

Comparison of CNN-LSTM with SVM and DNN for ALS/HC classification task

ALS/HC	SPON	DIDK	PHON
SVM	89.99(3.2)	94.52(4.3)	78.52(5.1)
DNN	92.44(3.1)	93.43(3.2)	78.80(4.3)
CNN-LSTM	**96.96(2.8)**	**94.60(2.7)**	**89.20(1.5)**

Table: Average (SD) accuracy of ALS/HC classification

Objectives of the experiments

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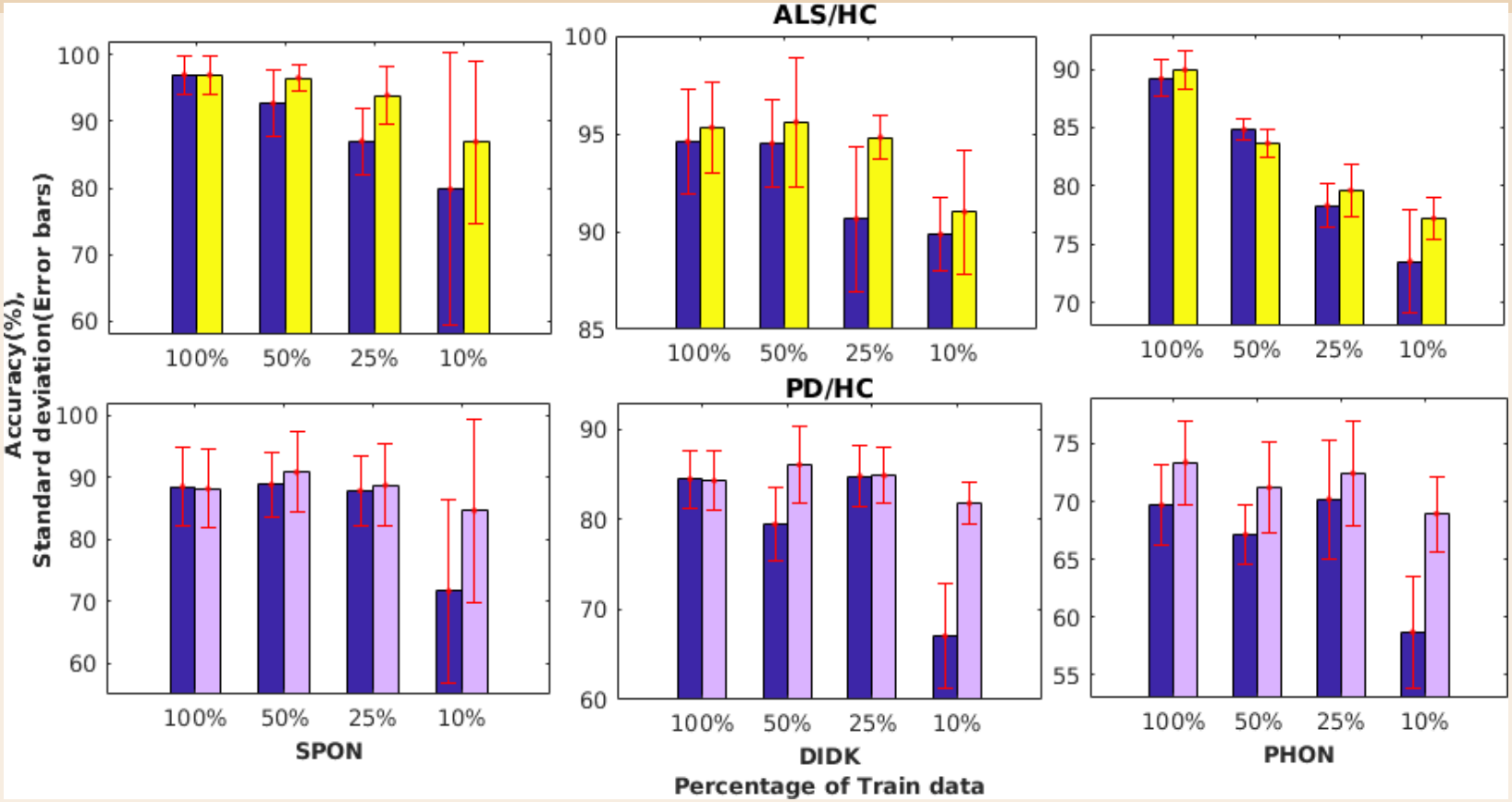
Transfer learning for ALS/HC and PD/HC with CNN-LSTM:



Classification accuracy by varying percentage of training data.

- RI, TL from PD/HC, TL from ALS/HC.

Objectives of the experiments

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- **3-class classification(ALS/PD/HC) with CNN-LSTM**.

Three class classification ALS/PD/HC using CNN-LSTM

		SPON	DIDK	PHON
3-class	ALS/PD/HC	83.04(2.17)	85.24(4.25)	77.20(1.95)
2-class	ALS/HC	95.2(2.33)	87(2.36)	86.1(1.0)
	PD/HC	90.7(3.94)	87(2.36)	74.1(5.67)
	ALS/HC (FT)	**98.22(1.87)**	95.5(1.72)	89.28(1.10)
	PD/HC (FT)	**90.98(4.03)**	84.62(5.69)	73.52(4.61)

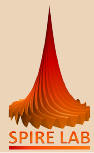
Table: Average accuracy (SD) of ALS/PD/HC model and pair-wise accuracy's of ALS/HC and PD/HC.

Overview

Key Takeaways

- CNN-LSTM works better than SVM and DNN for ALS/HC
- Transfer learning at low resource training data show that data from ALS benefits PD/HC classification and vice-versa
- Fine-tuning weights of 3-class (ALS/PD/HC) classifier for 2-class classification (PD/HC or ALS/HC) gives an absolute improvement of 2% classification accuracy in SPON task over random initialization.

Future work



- To investigate CNN-LSTM and transfer learning techniques for severity estimation of ALS and PD patients.
- To examine the scientific rationale behind such benefits due to PD in classification for ALS and vice-versa.

References

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Acknowledgement

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THANK YOU

Have Questions/Suggestions?
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