Dysphagia detection with Machine learning and Esophageal manometry

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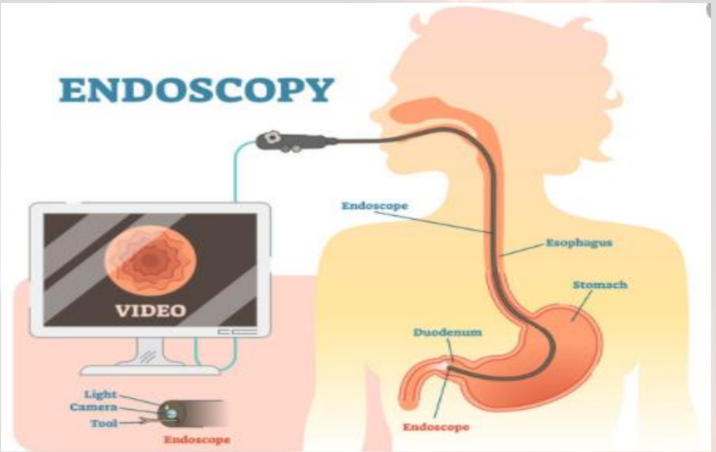
What is Dysphagia?

Dysphagia is a medical term for swallowing related problems.

How is Dysphagia Detected?

https://www.canterbury.ac.nz/rosecentre/research/publications/

X-RAY



https://www.health.harvard.edu/diseases-and-conditions/endoscopy

ENDOSCOPY

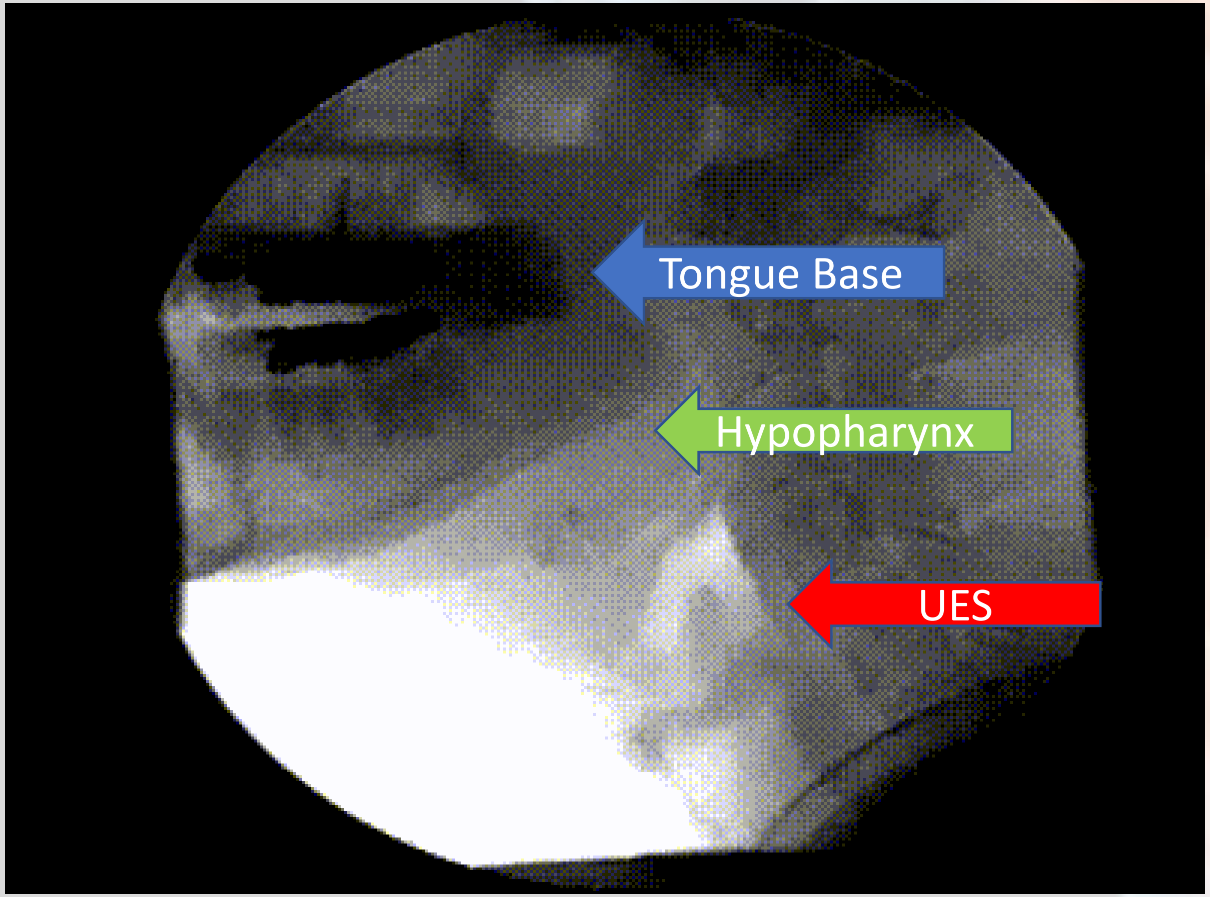
https://www.fmc-cares.com/esophageal-manometry-test/

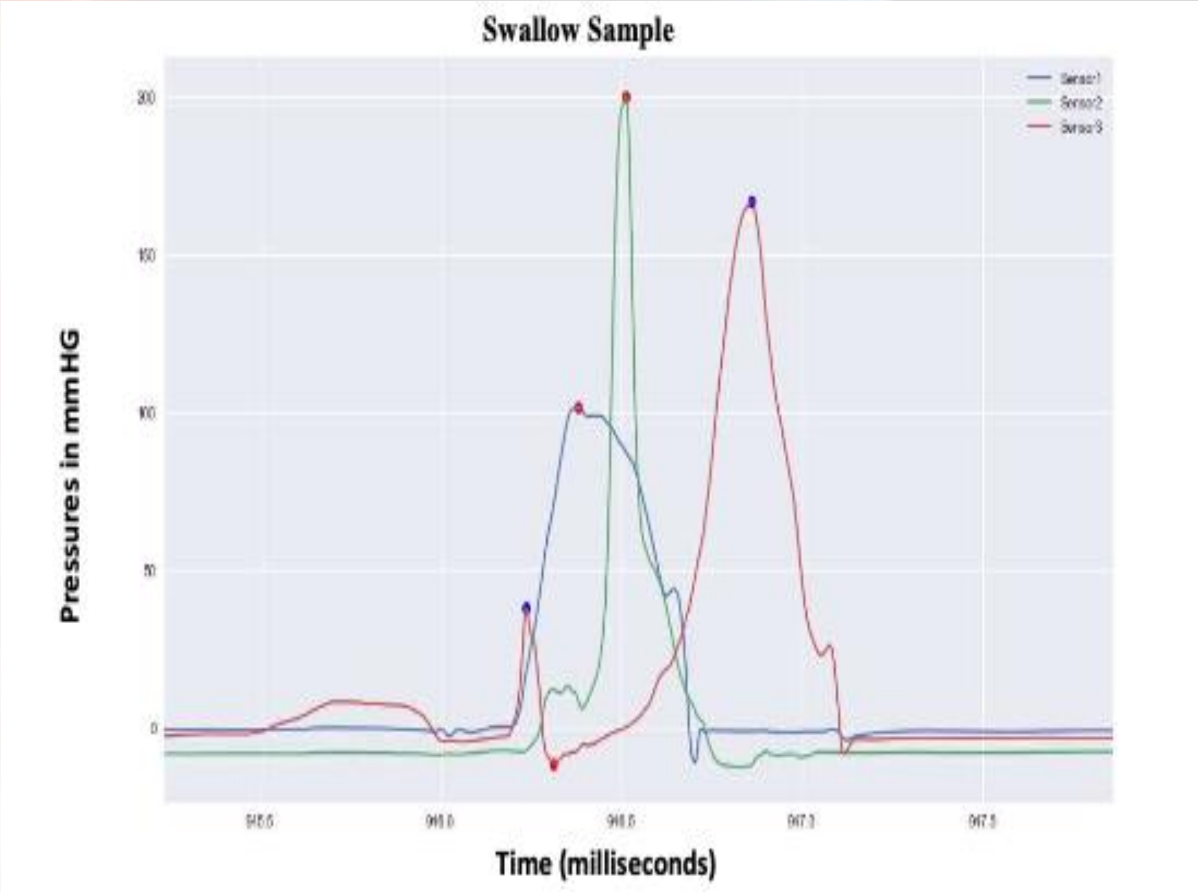
MANOMETRY

Limitations of Dysphagia detection Methods:

Time Consuming, exhaustive evaluation, costly, low detection rate.

What Happens when food is swallowed ?





What are we trying to achieve in this Research?

The main goal of this research is to combine the potential of an existing method for dysphagia detection i.e. Esophageal manometry and Machine learning with the following objectives

- To improve the Detection rate of Dysphagia
- To improve the efficiency of the detection process in terms of Time & resources required

What is Esophageal Manometry?

How does a Manometry Record of Patient Look like?

Manometry:		Sensor 1	Sensor 2	Sensor 3	SR: 1000 Hz	Units: mmHg
0	0.000000	140.510414	106.095216	15.456626		
1	0.001000	140.258640	105.587091	15.488670		
2	0.002000	140.482948		105.738155	15.433738	
3	0.003000	140.533303	105.614557	15.612268		
4	0.004000	140.194553	105.326162	15.282673		
5	0.005000	140.812543	105.623713	15.589380		
6	0.006000	140.345617	105.037766	15.438315		
7	0.007000	140.423438	105.143053	15.300984		
8	0.008000	140.377661	104.868391	15.424582		
9	0.009000	140.464637	104.799725	15.232319		
10	0.010000	140.876631	105.092699	15.534447		
11	0.011000	140.144198	104.419776	15.236896		
12	0.012000	140.492103	104.630350	15.378805		
13	0.013000	140.363928	104.328222	15.470359		
14	0.014000	140.469215	104.287022	15.259785		
15	0.015000	140.592813	104.406043		15.470359	
16	0.016000	139.842069	103.824674	15.076677		
17	0.017000	140.455482	104.122225	15.351339		
18	0.018000	140.222019	103.701076	15.461204		
19	0.019000	140.084688		103.691920	15.200275	
20	0.020000	140.139620	103.623255	15.374228		
21	0.021000	139.709316	103.087663	15.049210		
22	0.022000	140.254063	103.550011	15.328450		
23	0.023000	139.814603	102.904555	15.333028		
24	0.024000	139.787137	102.918288	15.186542		
25	0.025000	139.993133	102.881666	15.387961		
26	0.026000	139.787137	102.639048	15.177386		
27	0.027000	140.016022	102.758068	15.328450		
28	0.028000	139.192035	102.048524	15.058366		
29	0.029000	139.507897	102.249943	15.104143		
30	0.030000	139.700160	102.066835	15.383383		
31	0.031000	139.549096	101.865415	15.076677		
32	0.032000	139.732204	102.048524	15.273518		
33	0.033000	138.972305	101.352712	14.989700		
34	0.034000	139.416342	101.622797	15.195697		
35	0.035000	130.106612	101.270314	15.314717		

- Sensors record the pressure readings at intervals of 1 millisecond.
- Every second, 1000 readings are recorded by sensors.
- In this sample, there are close to 370,000 recordings, which means the length of the manometry session is 370 seconds(6 minutes)

Data Ethics

- Data collected for this research is composed of pressure readings from the patient's throat and do not contain any form of personal information on Patients such as name, age, or gender.

- It requires consent for anyone else to use it and responsible authority has issued consent only for this particular research.

- Any form of data collected during this research has been handled with complete integrity.

Constraints in Data collection

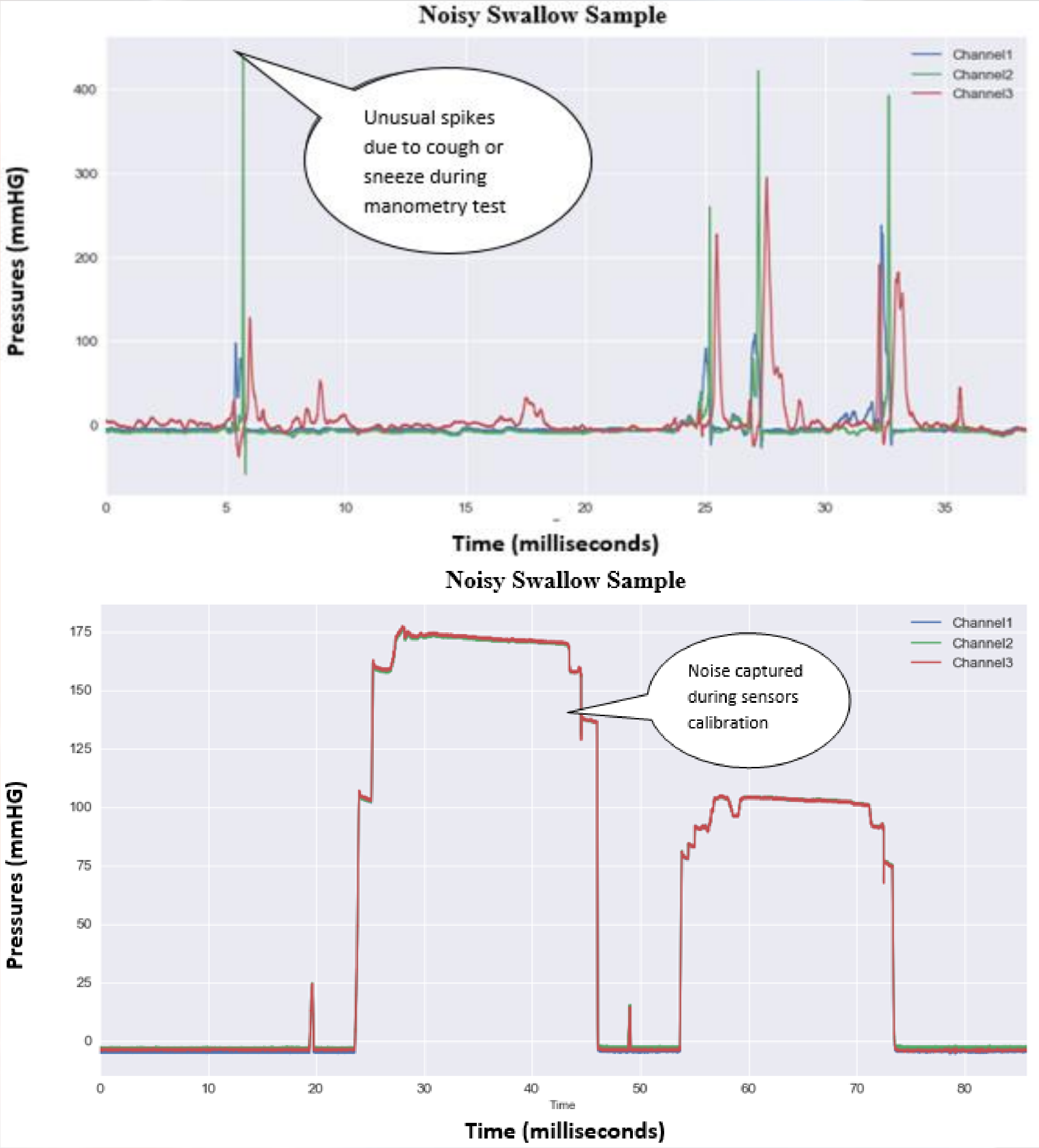
- Limited data availability
- Restriction to access important features such as patient's age, gender, height, or weight
- Limited data availability for different categories of patients such as Stroke, Parkinson's, Huntington disease
- Delays in data collection due to manometry system failure

Data Quality

Examples of Noise

<u>Noise Sources:</u>

- Sensors Calibration
- Patient experiencing cough or sneeze during manometry session
- Patient failing to comply with the guidelines of medical practitioner



Data Preprocessing & Sampling

Step.01

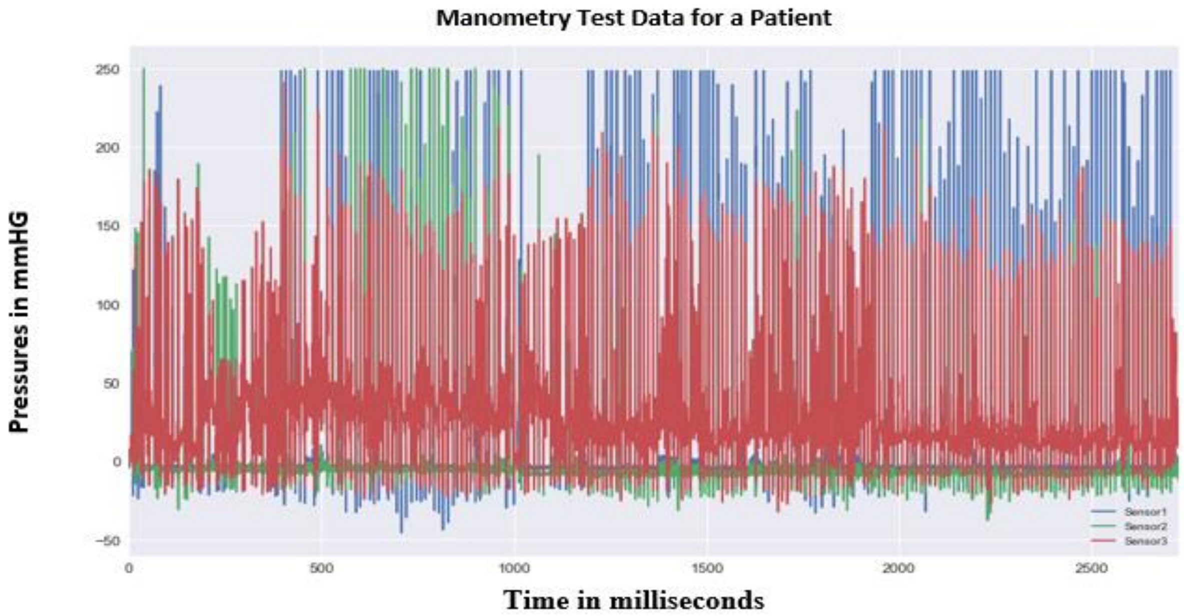
Transforming raw data into suitable format for plotting & Visualization

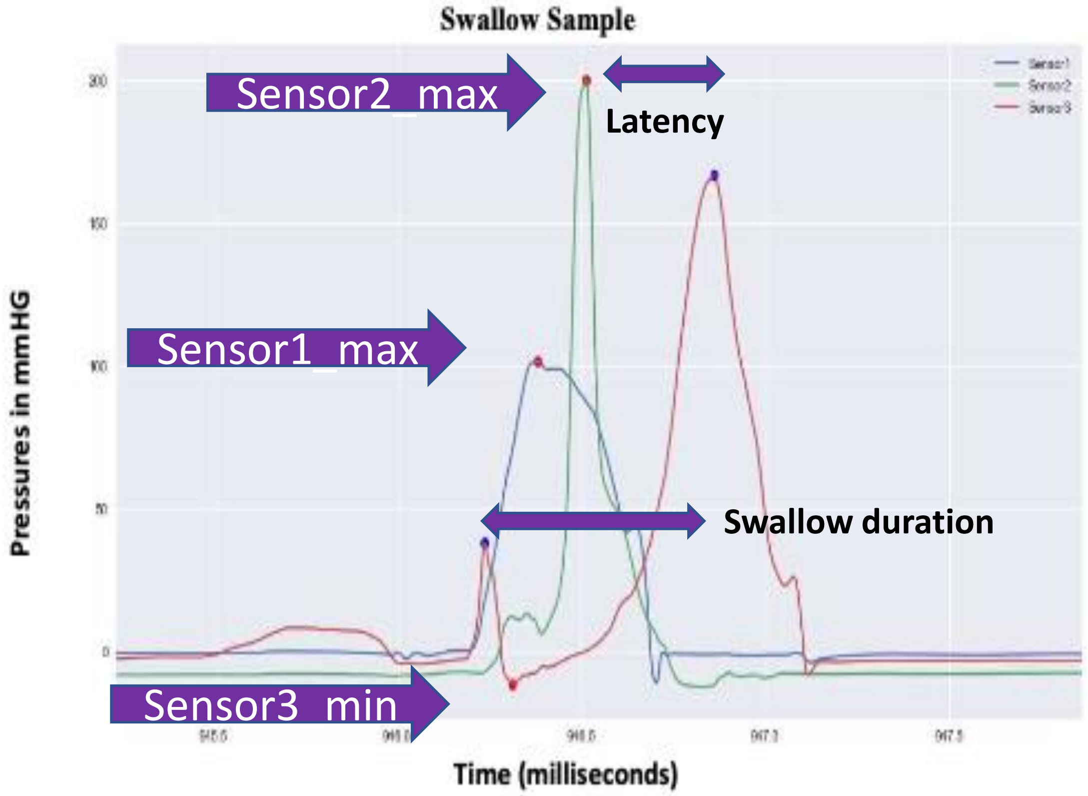
Step.02

Extracting swallow samples from the raw data

Step.03

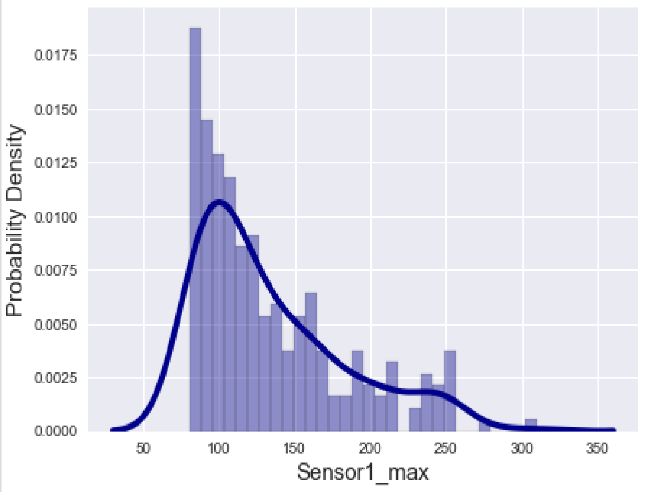
Evaluating features of a Sample

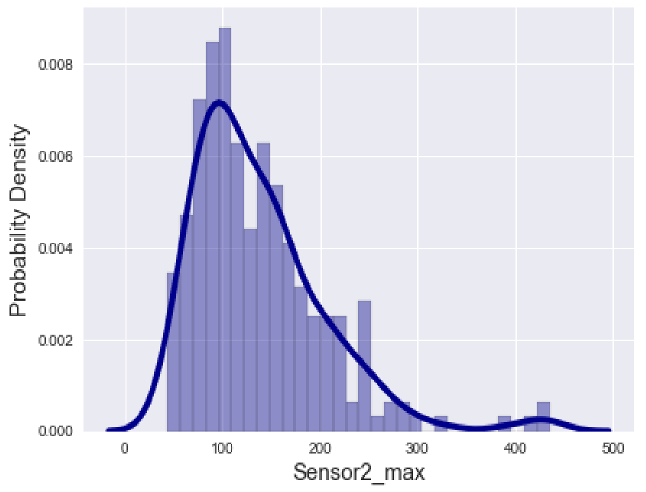


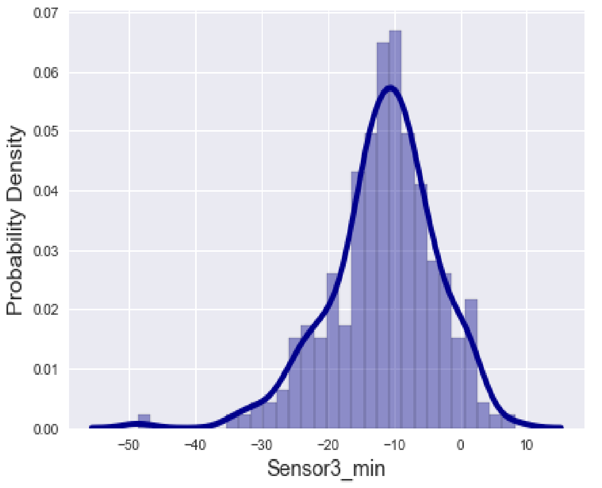


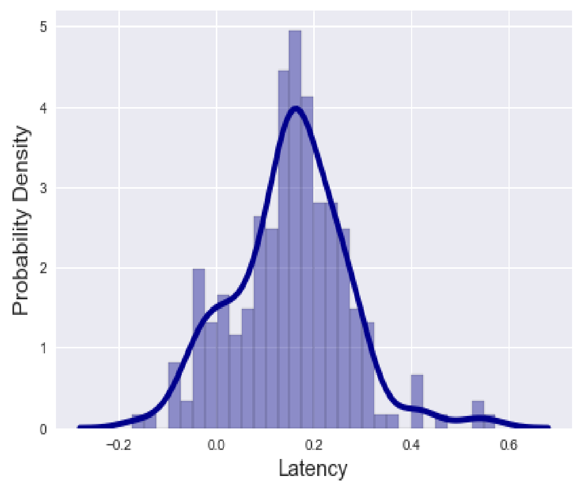
Exploratory Data Analysis

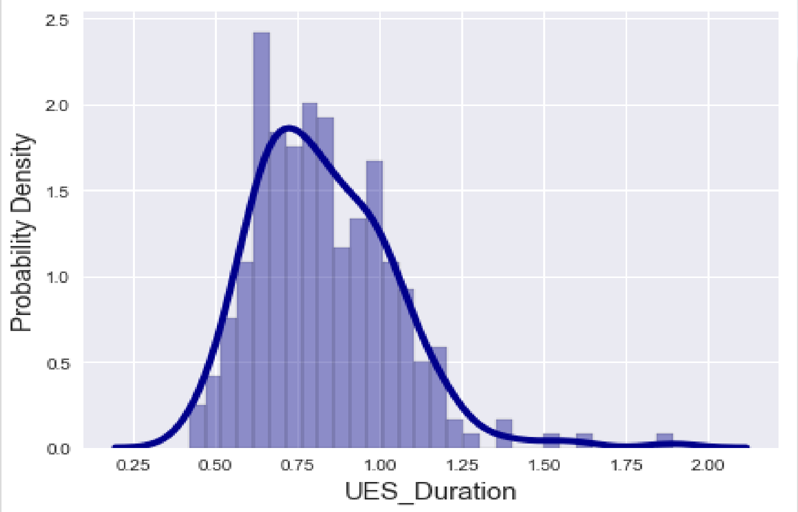
DENSITY PLOTS











CORRELATION MATRIX

	Sensor1_max	Sensor2_max	Sensor3_min	Latency	UES_Duration
Sensor1_max	1	-0.0346022	-0.038871	0.149575	0.0296155
Sensor2_max	-0.0346022	1	-0.124292	0.0283056	0.056447
Sensor3_min	-0.038871	-0.124292	1	-0.0584012	0.063469
Latency	0.149575	0.0283056	-0.0584012	1	0.316552
UES_Duration	0.0296155	0.056447	0.063469	0.316552	1

Data Modelling

Independent Features

Dependent Variable

	Patient	Sensor1_max	Sensor2_max	Sensor3_min	Latency	UES_Duration	Swallow type
0	Control 2.txt	101.393912	199.782559	-11.066606	0.132	0.624	Healthy
1	Control 2.txt	110.988785	143.783474	-9.734493	0.088	0.544	Healthy
2	Control 3.txt	164.236667	100.936141	-13.469902	0.268	0.812	Healthy
3	Control 3.txt	104.612039	186.672007	-17.383841	0.248	0.988	Healthy
4	Control 5.txt	113.895628	158.551156	-14.614328	0.088	0.644	Healthy
5	HF1-E.txt	137.317464	119.958801	-11.723507	0.309	0.792	Healthy
6	HF10-HL.txt	108.303960	45.131609	-13.014420	0.079	0.716	Healthy

Train and Test Data Composition

Composition	Training data	Testing data	Total
No of Healthy swallow samples	86	38	124
No of Unhealthy swallow samples	84	36	120
Total samples	170	74	244

Performance of models trained to detect unhealthy patients

The evaluation metrics for classification models are shown below:

S. No	Classification Model	Default Hyperparameters			Hyperparameter tuning with 6 fold cross validation		
		Accuracy	Precision	Recall	Accuracy	Precision	Recall
1	Logistic Regression	68%	65%	72%	66%	63%	72%
2	Support Vector Classifier	54%	67%	11%	69%	70%	64%
3	Random Forest Classifier	69%	68%	69%	61%	58%	69%
4	XGBoost Classifier	66%	62%	78%	62%	60%	69%
5	LightGBM Classifier	58%	66%	67%	68%	65%	72%

Performance of the models trained for screening of patients

Logistic Regression	Precision	Recall
Healthy	1.00	0.21
Unhealthy	0.55	1.00

Random Forest	Precision	Recall
Healthy	1.00	0.21
Unhealthy	0.55	1.00

Support Vector	Precision	Recall
Healthy	1.00	0.03
Unhealthy	0.51	1.00

XGBoost Classifier	Precision	Recall
Healthy	1.00	0.24
Unhealthy	0.55	1.00

LightGBM Classifier	Precision	Recall
Healthy	1.00	0.13
Unhealthy	0.52	1.00

The probability threshold was regulated to achieve 100% recall for the Unhealthy class and 100% precision for the healthy class. These models can facilitate the screening of patients and save the cost and resources by 21-24%.

Conclusion

- The best performing models i.e. Logistic regression and LightGBM classifier were able to detect 72% of unhealthy patients.
- Support Vector, Random forest & XGBoost classifiers displayed a detection rate of 64%, 69% & 69% respectively.
- XGBoost, Random forest & Logistic regression has potential to save the cost & resources by 24%, 21% & 21% respectively.
- LightGBM & Support vector classifier displayed a potential to save cost & resources by 13% & 3% respectively.
- Overall, Logistic regression & Light GBM are the best performing models for the detection of unhealthy patients. However, for the screening process, XGBoost performs the best.

Future Work

- This research utilizes data from high-resolution manometry, however, this data can be collected by using advanced techniques like high definition manometry, which has a better spatial resolution.

- Sampling process can be improved by collecting samples from different types of swallows such as “Saliva swallow”, “10ml bolus swallow” and “Effortful swallow”