

# NEUROTONE.AI

Diversifying detection of parkinson's disease through multilingual non-invasive audio data

# LITERATURE REVIEW

Early diagnosis in PD, does it even make a difference?

Voice problems are typically the first to occur, while other disorders, such as prosody, articulation and fluency, appear later and gradually [7]–[9]. The majority of the individuals developing the disease are aged, but the disease sometimes develops in young people. Given that the disease progression is relatively slow, the chance that these individuals could maintain a good quality of life is increased by their improvement in the communication ability. Therefore, the value of an effective treatment for disordered communication is high.

lion people in North America alone [3]. Moreover, an aging population means this number is expected to rise as studies suggest rapidly increasing prevalence rates after the age of 60 [4]. In addition to increased social isolation, the financial burden of PD is significant and is estimated to rise in the future [5]. Currently, there is no cure, although medication is available offering significant alleviation of symptoms, especially at the early stages of the disease [6]. Most *people with Parkinson's* (PWP) disease will therefore be substantially dependent on clinical intervention.

In essence Early diagnosis enables:

1. Better Quality of Life
2. Lowering Financing burden
3. Prepares us for an aging population
4. Prevents progression of disease

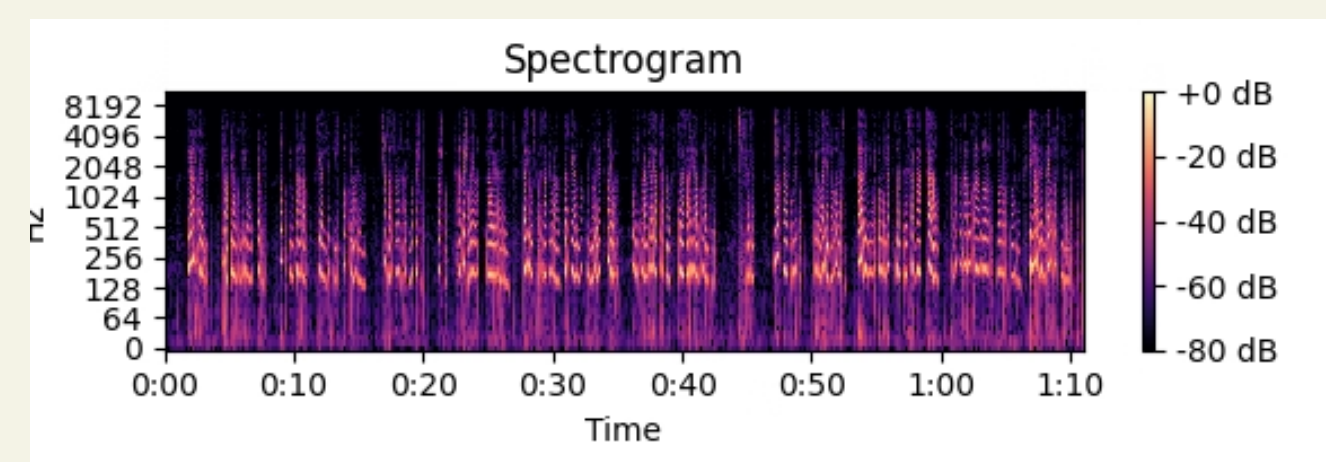
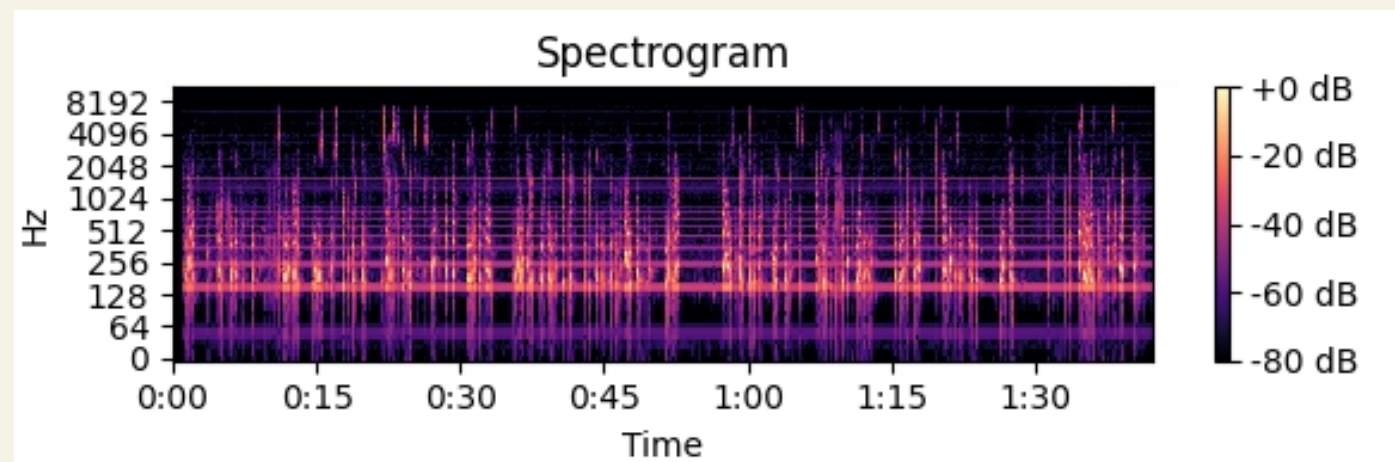
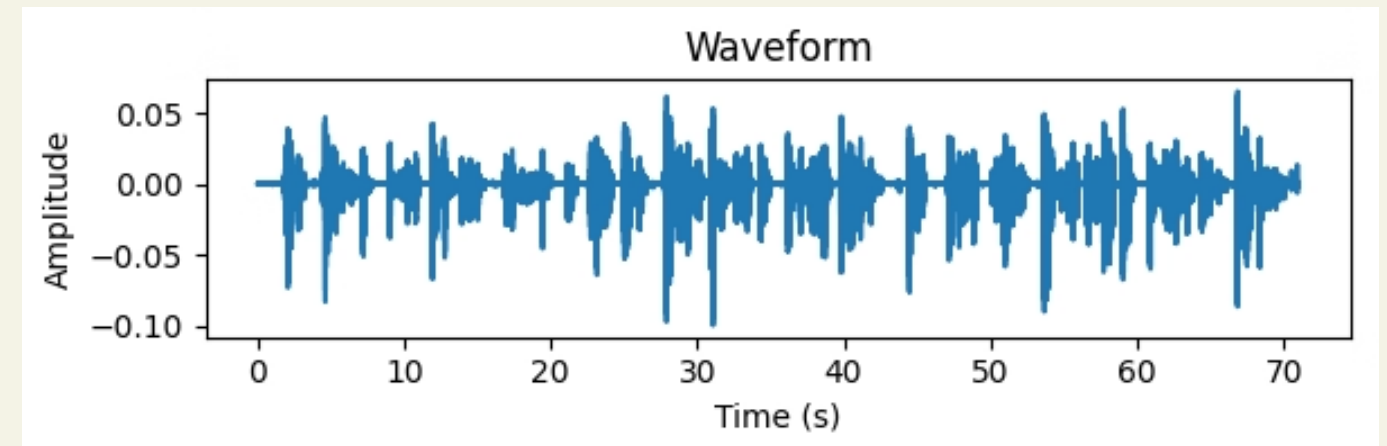
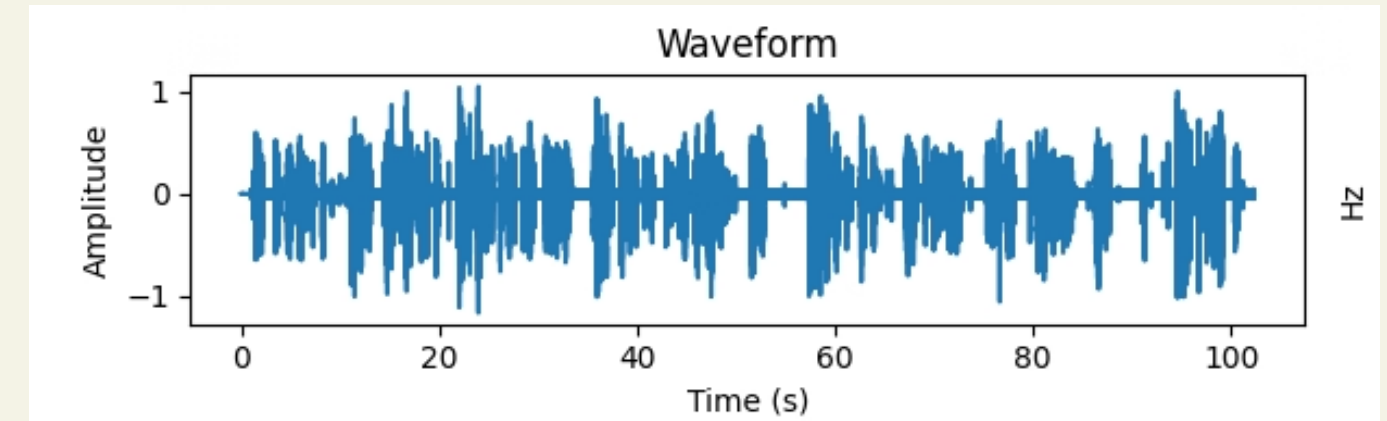
# LITERATURE REVIEW

## Why Sound and How?

diagnose PD at the preclinical stage, biomarkers are usually searched in BF in untreated PD patients at the clinical stage. Although dozens of studies have attempted to identify biomarkers in BF, most of the results are contradictory. Nevertheless, some changes in the level

Acoustic data collection is:

1. Non invasive
2. Cheap
3. Prevalent in 90% of the patients



# PROBLEM STATEMENT

AI models currently, diagnose Parkinson but they only do so for monolingual data. hence, creating a lack of diversity in their use case

# PRE MIDSEM DEVELOPMENT

# OUR DATASET

1. Two Datasets
2. Sustained Phonetics technique
3. Demographics:
  - a. 81 italians
  - b. 31 English speakers
4. Control and Diagnosed
  - a. 23 ENG PD
  - b. 28 ITA PD
5. 25 Features
6. Datapoints: 978\*

## Second Dataset

- f. 15 Young Healthy Control (Running Speech data is available)
- g. 22 Health Elderly Control (Both Running Speech and Sustained Data is present)
- h. 28 people with Parkinson's disease (Both Running Speech and Sustained Data is present)

LIST OF SUBJECTS WITH SEX, AGE, PARKINSON'S STAGE, AND NUMBER OF YEARS SINCE DIAGNOSIS

Subject code	Sex	Age	Stage (H&Y)	Years since diagnosis
S01	M	78	3.0	0
S34	F	79	2.5	¼
S44	M	67	1.5	1
S20	M	70	3.0	1
S24	M	73	2.5	1
S26	F	53	2.0	1½
S08	F	48	2.0	2
S39	M	64	2.0	2
S33	M	68	2.0	3
S32	M	50	1.0	4
S02	M	60	2.0	4
S22	M	60	1.5	4½
S37	M	76	1.0	5
S21	F	81	1.5	5
S04	M	70	2.5	5½
S19	M	73	1.0	7
S35	F	85	4.0	7
S05	F	72	3.0	8
S18	M	61	2.5	11
S16	M	62	2.5	14
S27	M	72	2.5	15
S25	M	74	3.0	23
S06	F	63	2.5	28
S10 (healthy)	F	46	n/a	n/a
S07 (healthy)	F	48	n/a	n/a
S13 (healthy)	M	61	n/a	n/a
S43 (healthy)	M	62	n/a	n/a
S17 (healthy)	F	64	n/a	n/a
S42 (healthy)	F	66	n/a	n/a
S50 (healthy)	F	66	n/a	n/a
S49 (healthy)	M	69	n/a	n/a

# FEATURE EXTRACTION

## FEATURE EXTRACTION

Calculate fundamental frequency (F0)

1. Average, maximum, and minimum F0
2. Jitter (percent and absolute)
3. Relative Amplitude Perturbation (RAP)
4. Pitch Period Perturbation Quotient (PPQ)

Extract F0 contour and calculate:

1. Spread 1 and Spread 2 (quantile differences)
2. Pitch Period Entropy (PPE)
3. Calculate RPDE and D2 from F0 contour

Calculate amplitude envelope and related features:

1. Shimmer (APQ3, APQ5, MDVP)
2. Jitter (DDP)
3. Amplitude Perturbation Quotient (APQ)
4. Shimmer Dda
5. Noise-to-Harmonic Ratio (NHR) and Harmonic-to-Noise Ratio (HNR)

# DATA PRE PROCESSING

Person	Wav file	MDVP:Fo(Hz)	MDVP:Fhi(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)	MDVP:Jitter(Abs)	MDVP:RAP	MDVP:PPQ	Shimmer:APQ3	Shimmer:APQ5
Giulia P	GLL63F10022017	200.403	308.791	75.0	14.667	6.302	6.302	8.604	0.001	0.003
Giulia P	GLL63F1002201	238.239	245.087	232.672	1.115	0.474	0.474	0.811	0.005	0.007
Giulia P	IGLL63F1002201	196.541	250.816	75.0	30.619	1.149	1.149	1.785	0.001	0.003
Giulia P	IGLL63F1002201	205.433	240.877	180.454	2.778	1.244	1.244	1.43	0.005	0.013

name	rep	MDVP:Fo(Hz)	MDVP:Fhi(Hz)	MDVP:Flo(Hz)	MDVP:Jitter(%)	MDVP:Jitter(Abs)	MDVP:RAP	MDVP:PPQ	Jitter:DDP	MDVP:Shimmer I
phon_R01_S01	1	119.992	157.302	74.997	0.008	0.0	0.004	0.006	0.011	0.044
phon_R01_S01	2	122.4	148.65	113.819	0.01	0.0	0.005	0.007	0.014	0.061
phon_R01_S01	3	116.682	131.111	111.555	0.01	0.0	0.005	0.008	0.016	0.052
phon_R01_S01	4	116.676	137.871	111.366	0.01	0.0	0.005	0.007	0.015	0.055

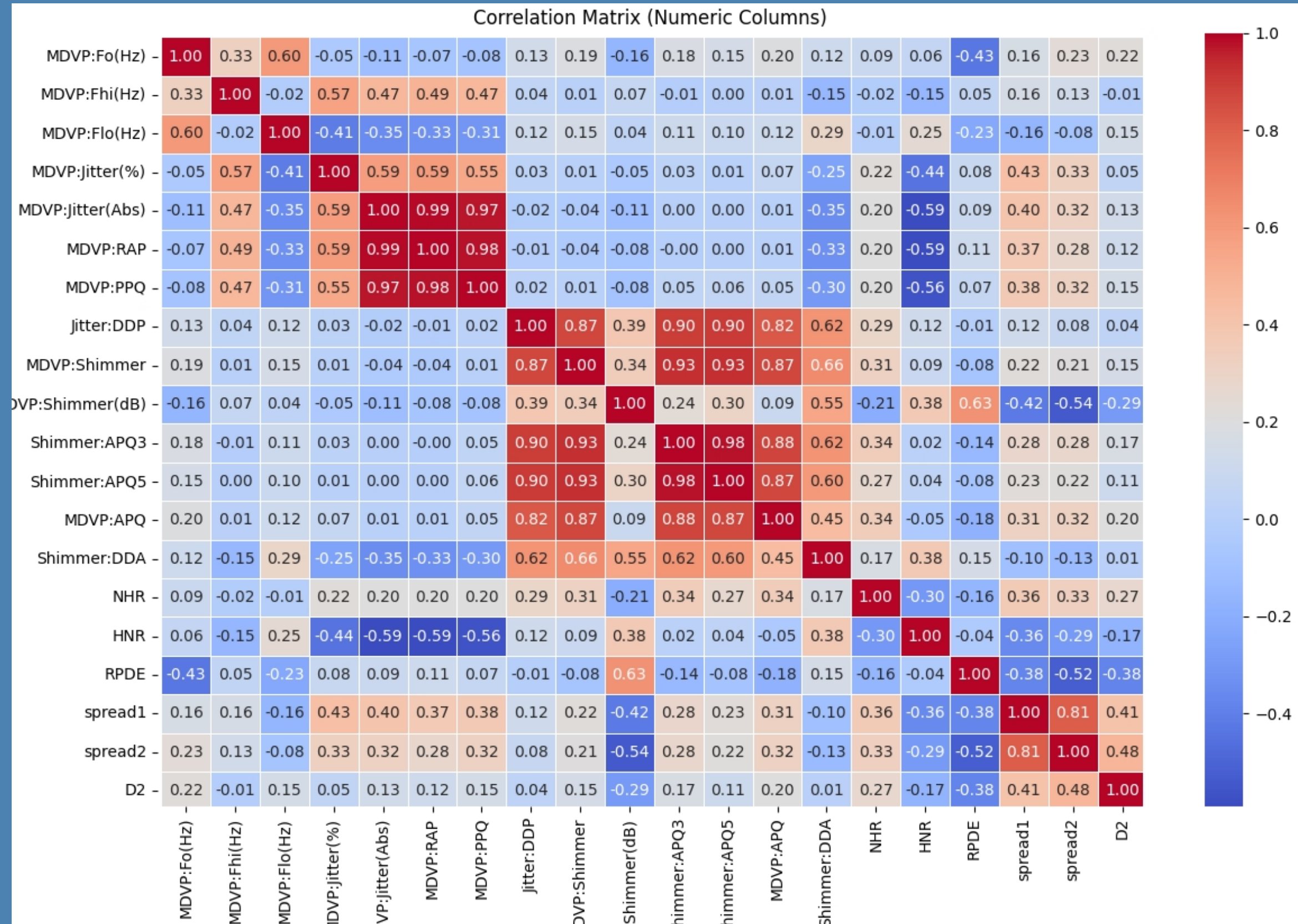


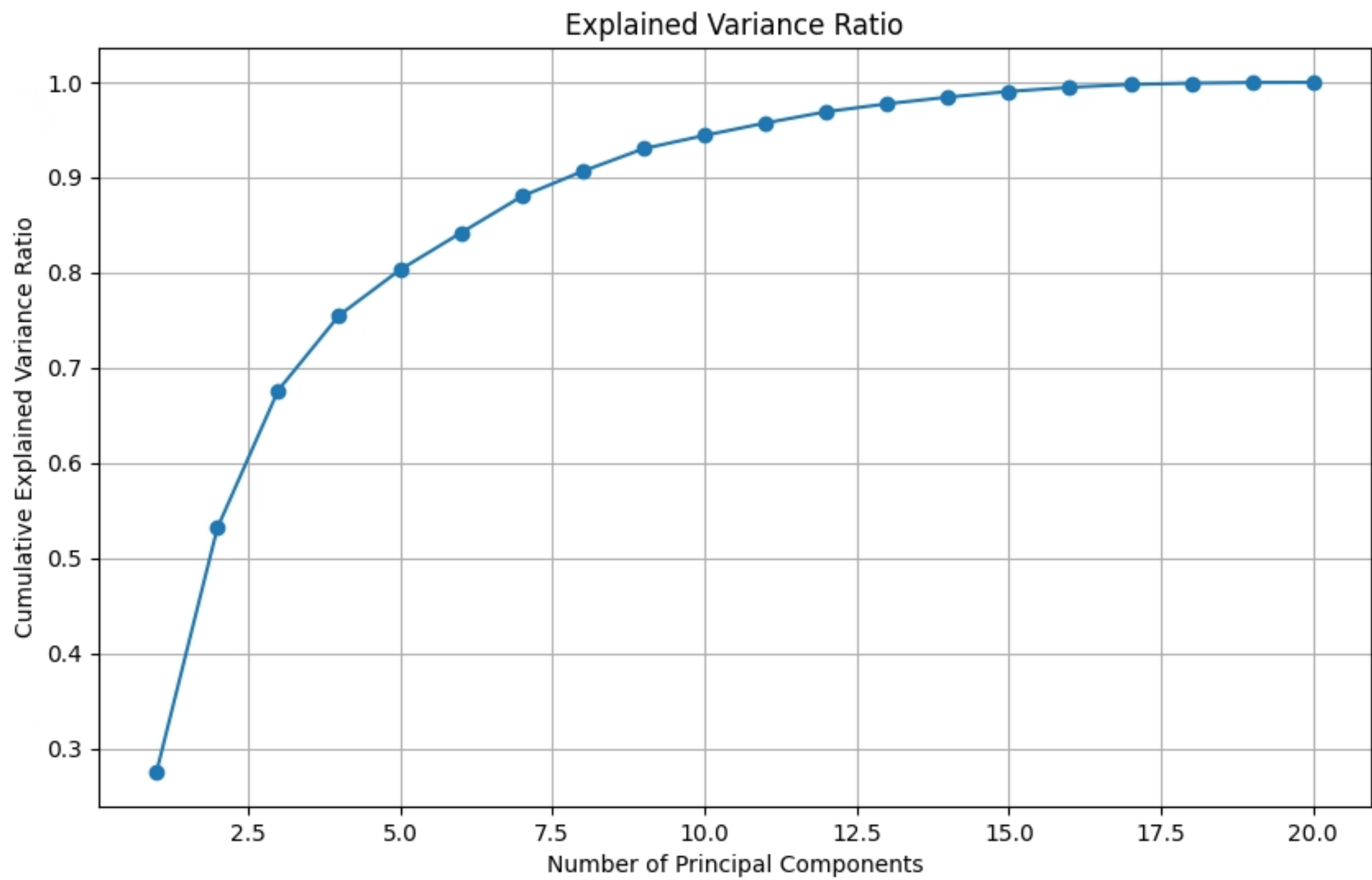
# DATA COMBINING

Shimmer:DDA	NHR	HNR	status	RPDE	spread1	spread2	D2	Language
3325844139170606830696756533	.5117451028204		1	.36915542219557	56987520957057	58576512936186	39066128438146	English
5160482732058005933093548079	43257742014142		1	.4708304847858	70327699403701	74133704321517	47314522027094	English
4433174990371003959639685520	49622043404047		1	.4044159680433	63674469842719	68637091164493	4088193790738	English
4754782385415004099691249960	49593595058115		1	41625503697084	69562749855223	73808864546541	43697717125738	English

.257234947123731871497459318E	75335957189575		0	1	01089159070027	.0102017330069	00329700403551	Italian
.690466396661543580651284006E	.82113378433232		0	1	00871572692921	00788445904606	00306578557694	Italian
.690017076860225610239278084E	.73832116189538		0	1	00882517835645	00766417180344	00285253858471	Italian
0	0043974613262305067742510048		0	1	05053649318806	03696840656772	.12171065337609	Italian
.344517349361137482841901068E	.7472438382537		0	1	00935264955046	00806842931848	00320306482026	Italian

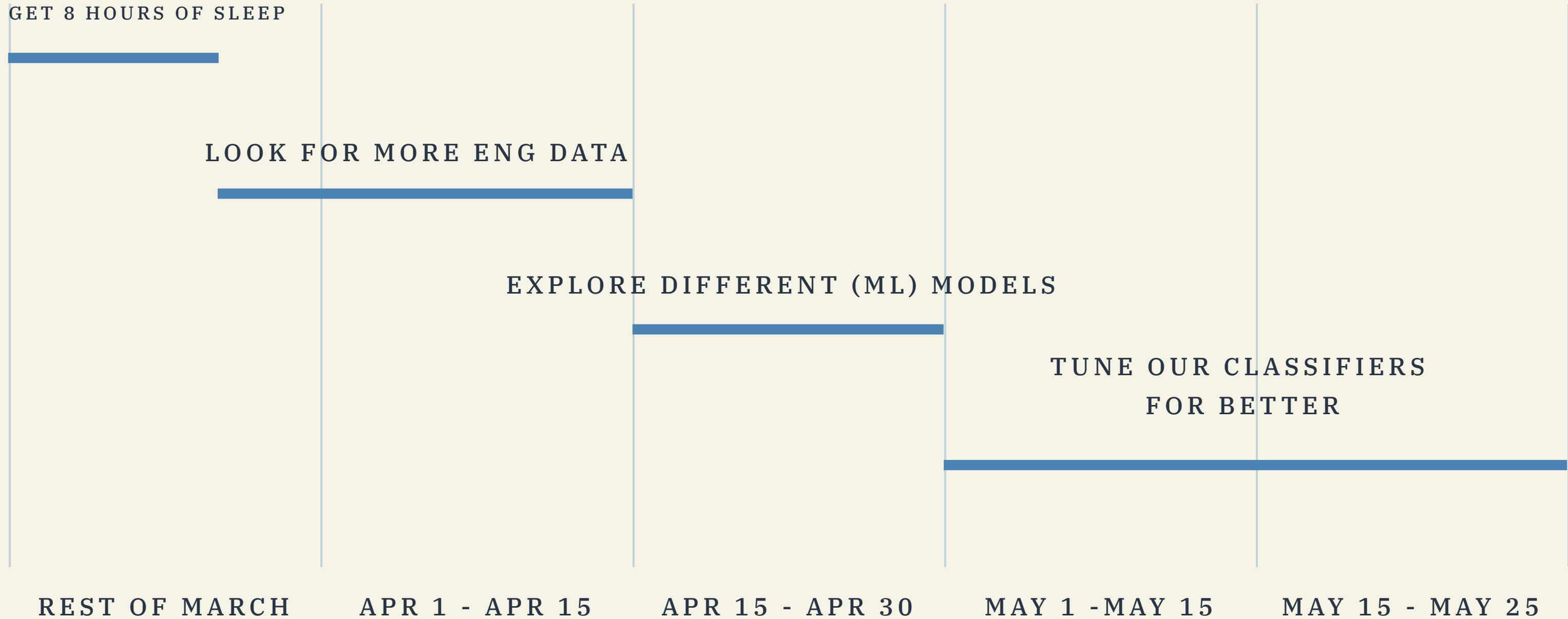
# ANALYSIS





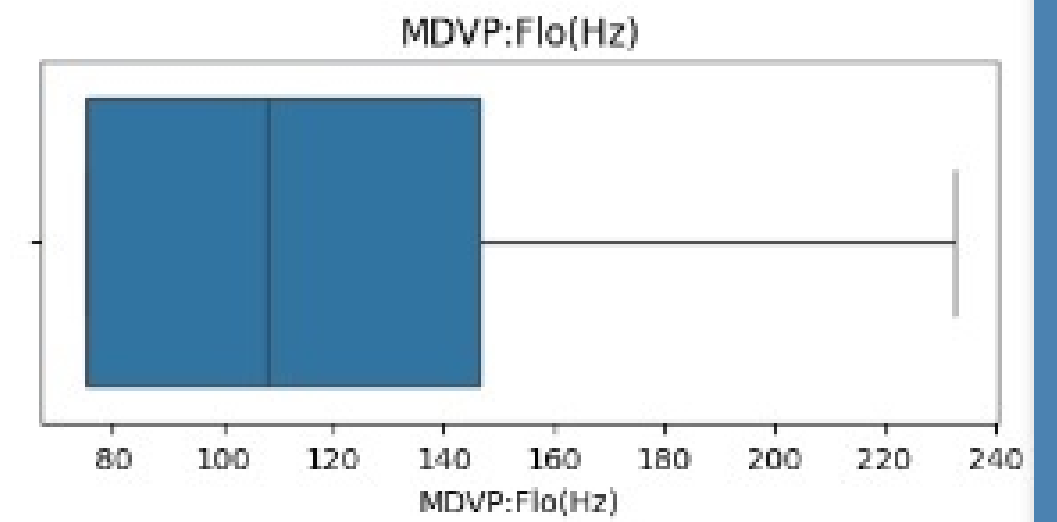
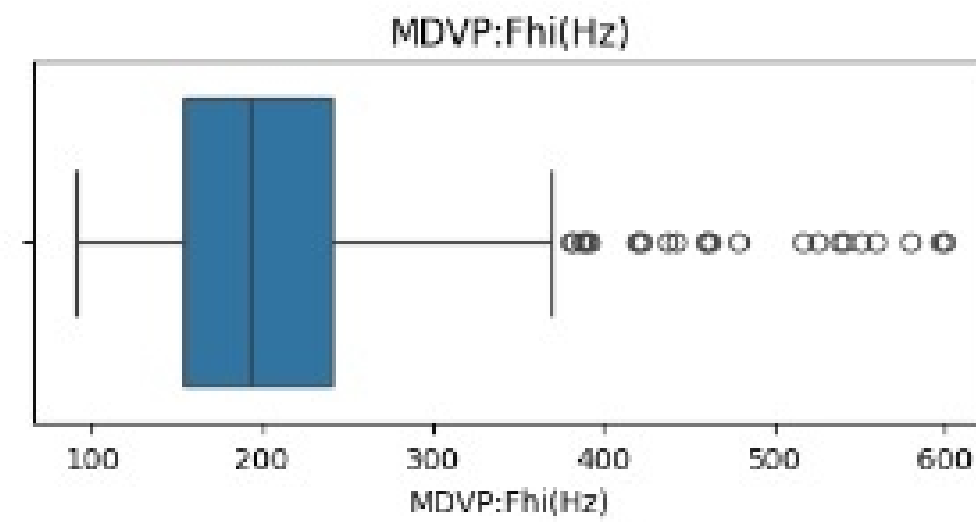
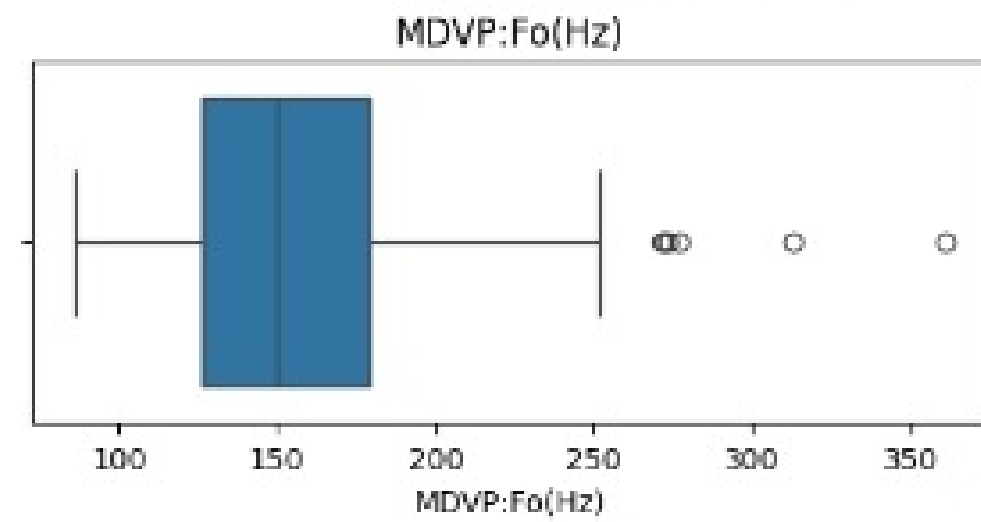
# Timeline for the semester

- THROW COLORS ON PEOPLE WALKING BY
- EAT HOMECOOKED FOOD
- FINALLY GET 8 HOURS OF SLEEP

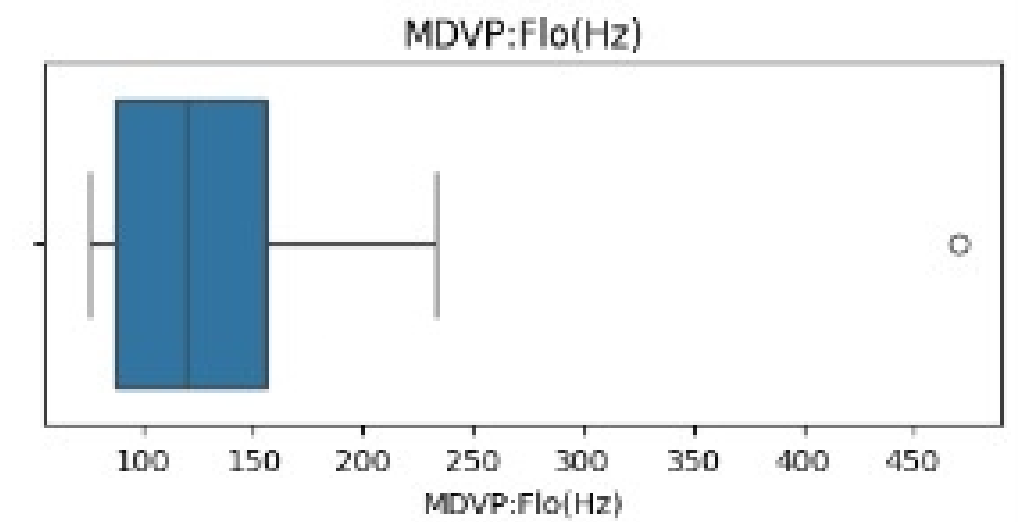
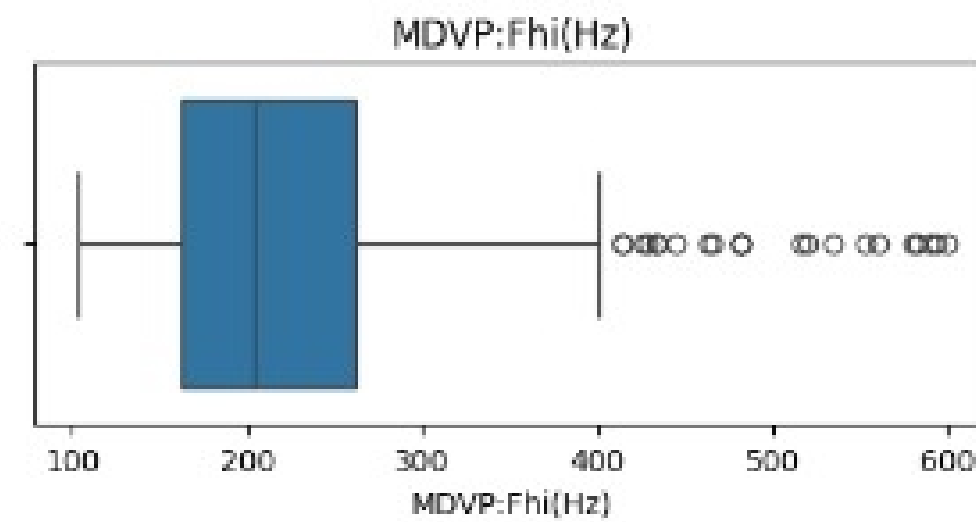
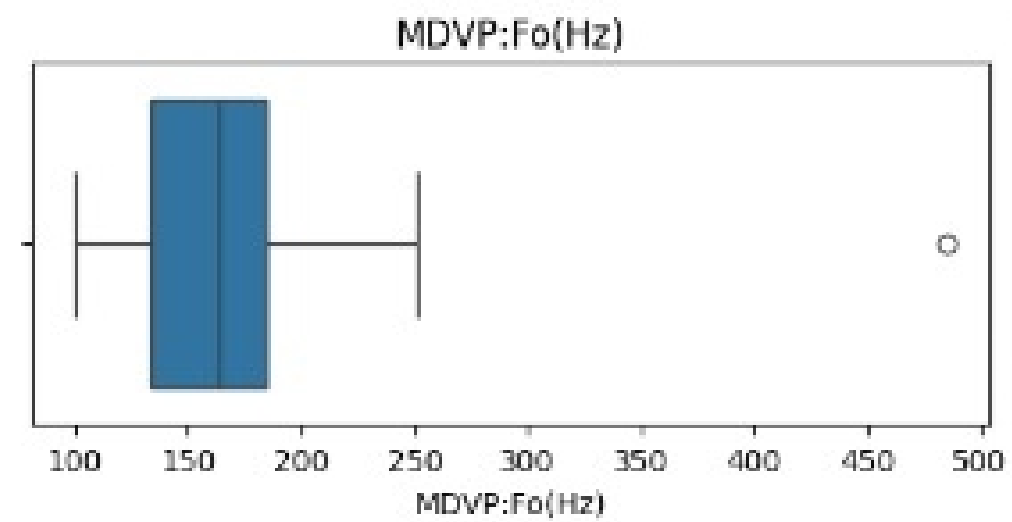


# POST MIDSEM DEVELOPMENT

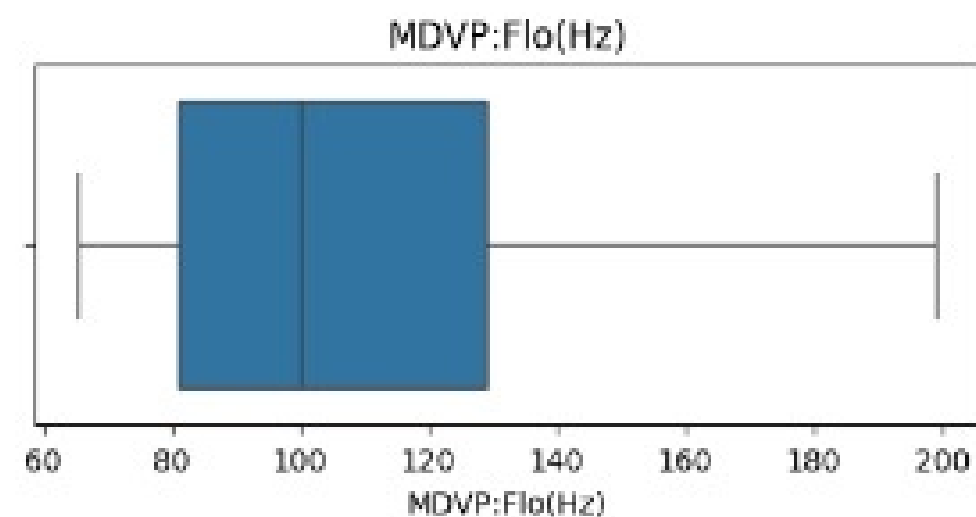
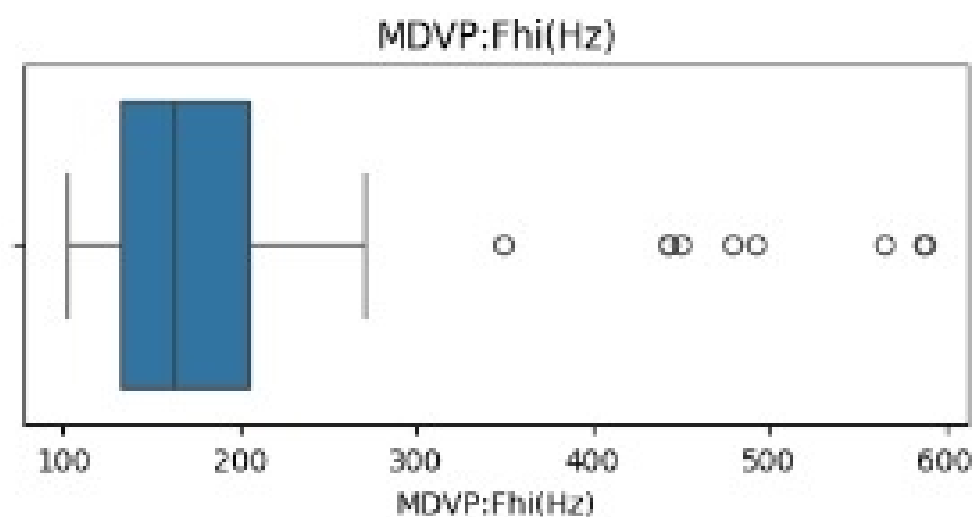
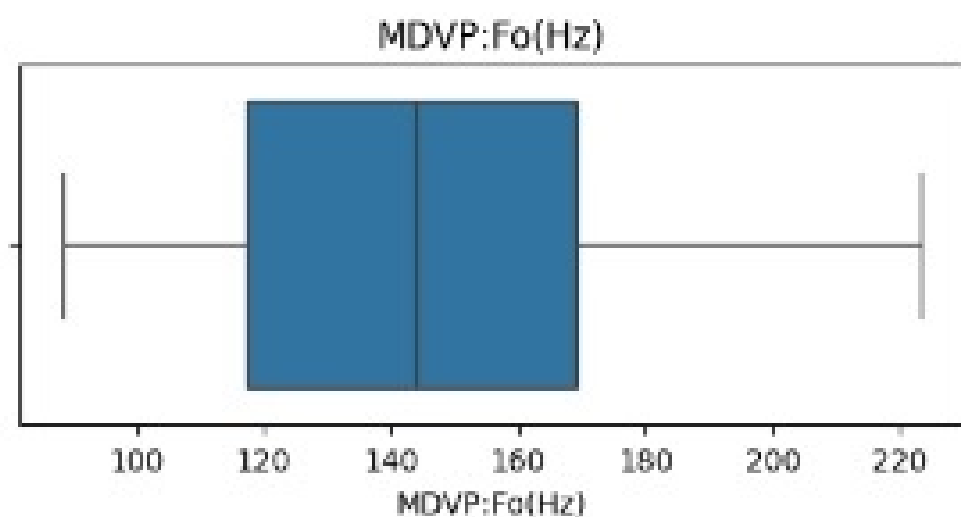
Outliers for Italian Data with parkinson:



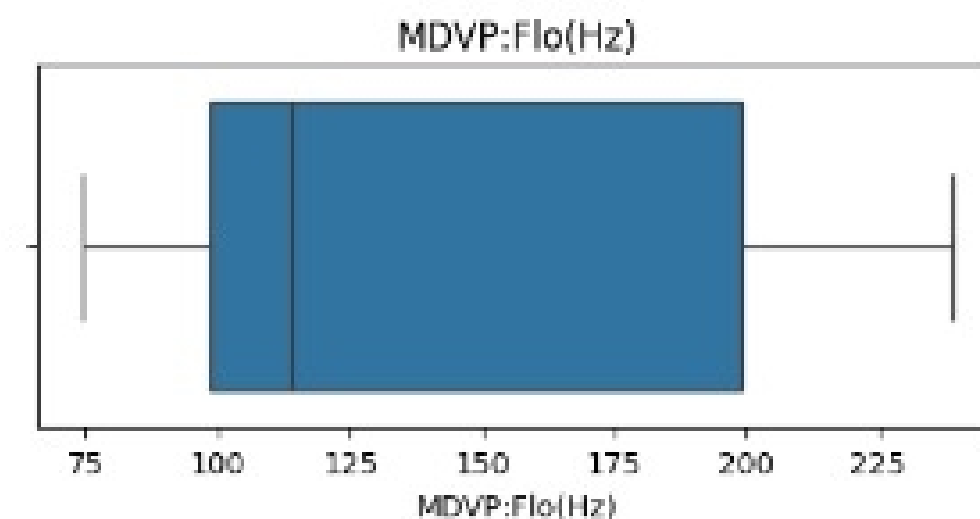
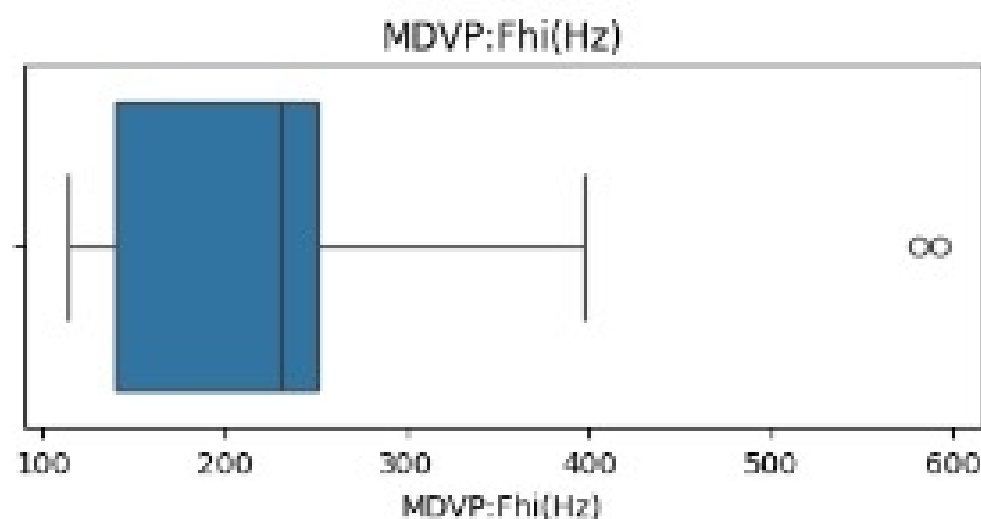
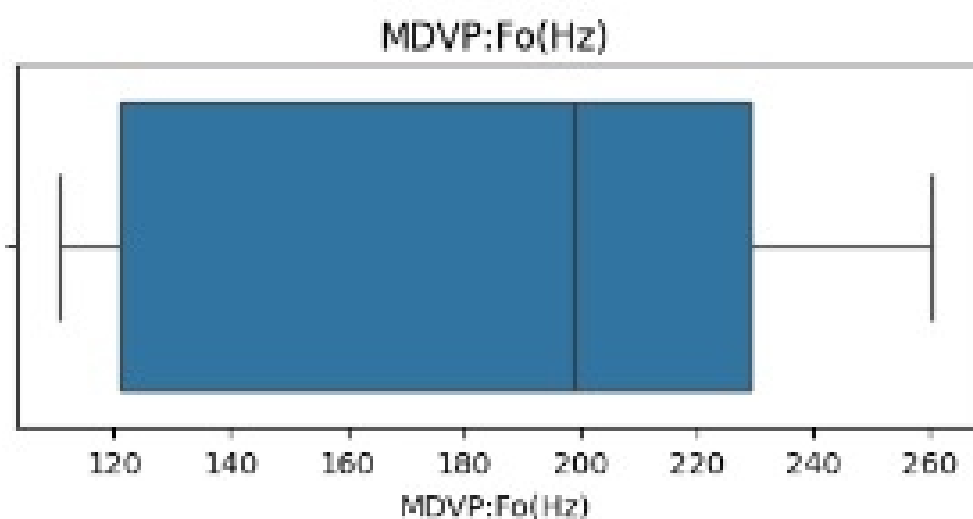
Outliers for Italian Data without parkinson:

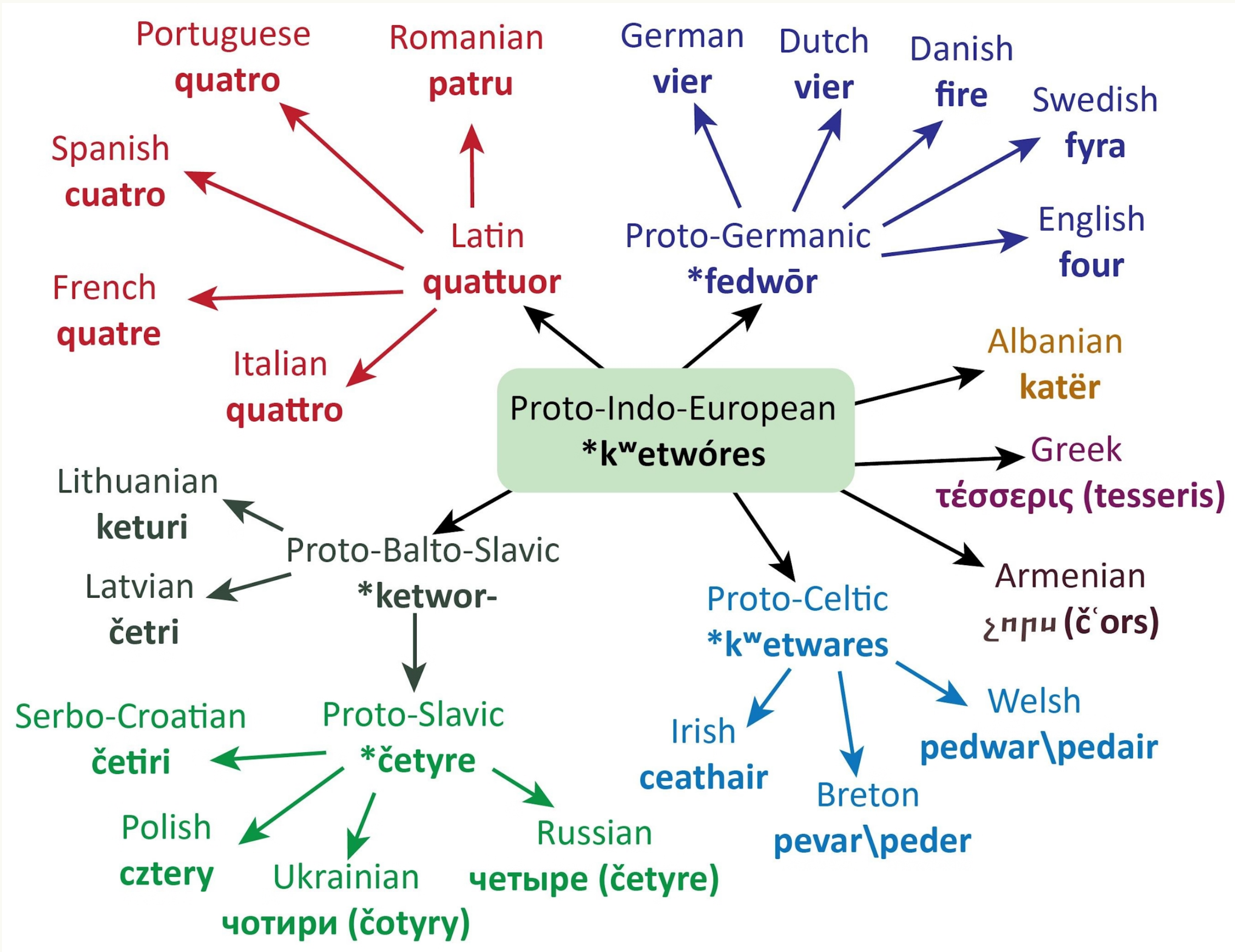


Outliers for English Data with parkinson:



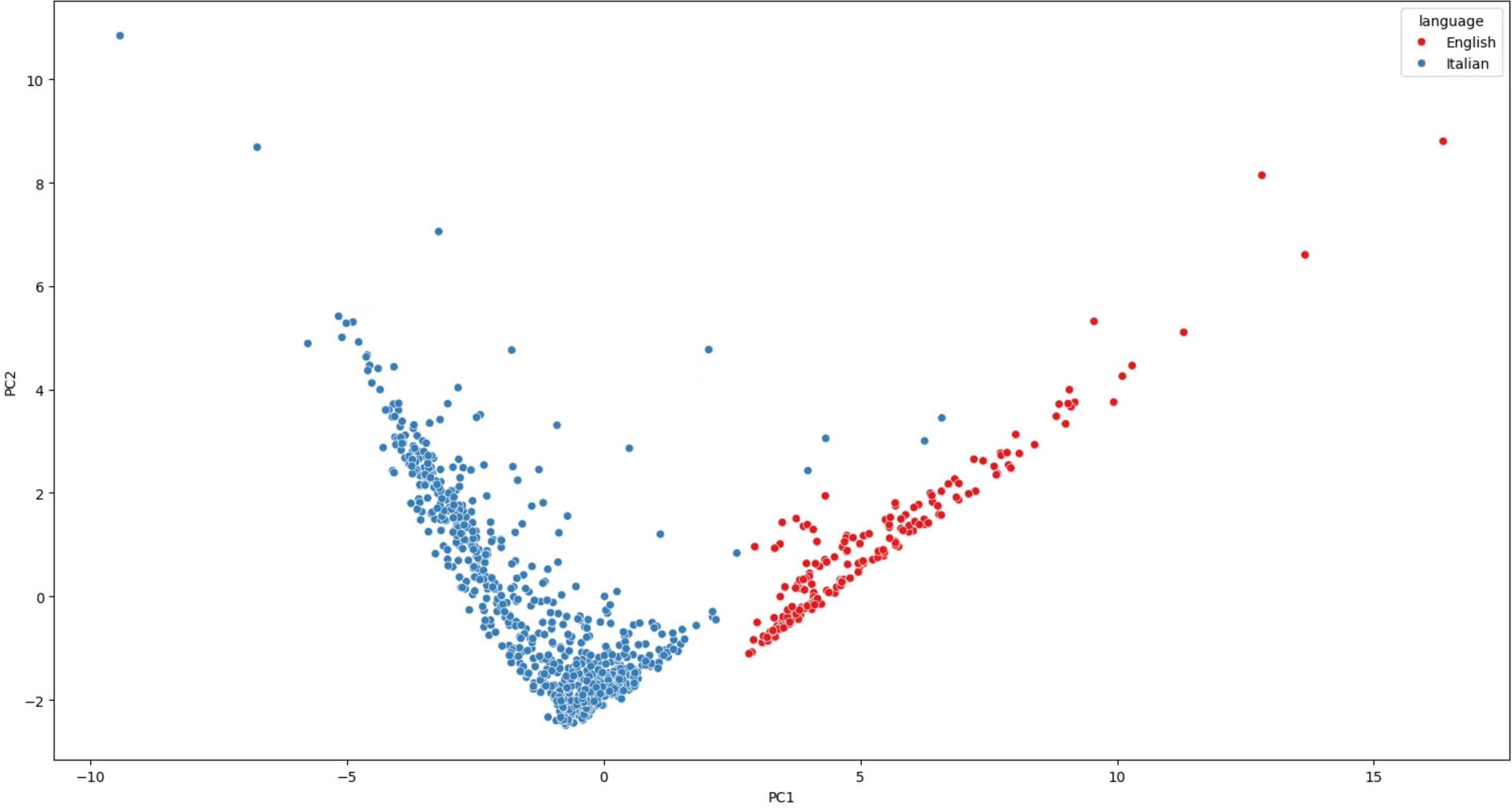
Outliers for English Data without parkinson:







Plot showing that both datasets are inherently different



# Early Diagnosis of Parkinson's Disease via Machine Learning on Speech Data

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**Abstract**— Using two distinct data sets (from the USA and Germany) of healthy controls and patients with early or mild stages of Parkinson's disease, we show that machine learning tools can be used for the early diagnosis of Parkinson's disease from speech data. This could potentially be applicable before physical symptoms appear. In addition, we show that while the training phase of machine learning process from one country can be reused in the other; different features dominate in each country; presumably because of languages differences. Three results are presented: (i) **separate training and testing** by each country (close to **85%** range); (ii) **pooled training and testing** (about **80%** range) and (iii) cross-country (training in one and testing in the other) (about **75%** ranges). We discovered that different feature sets were needed for each country (language).

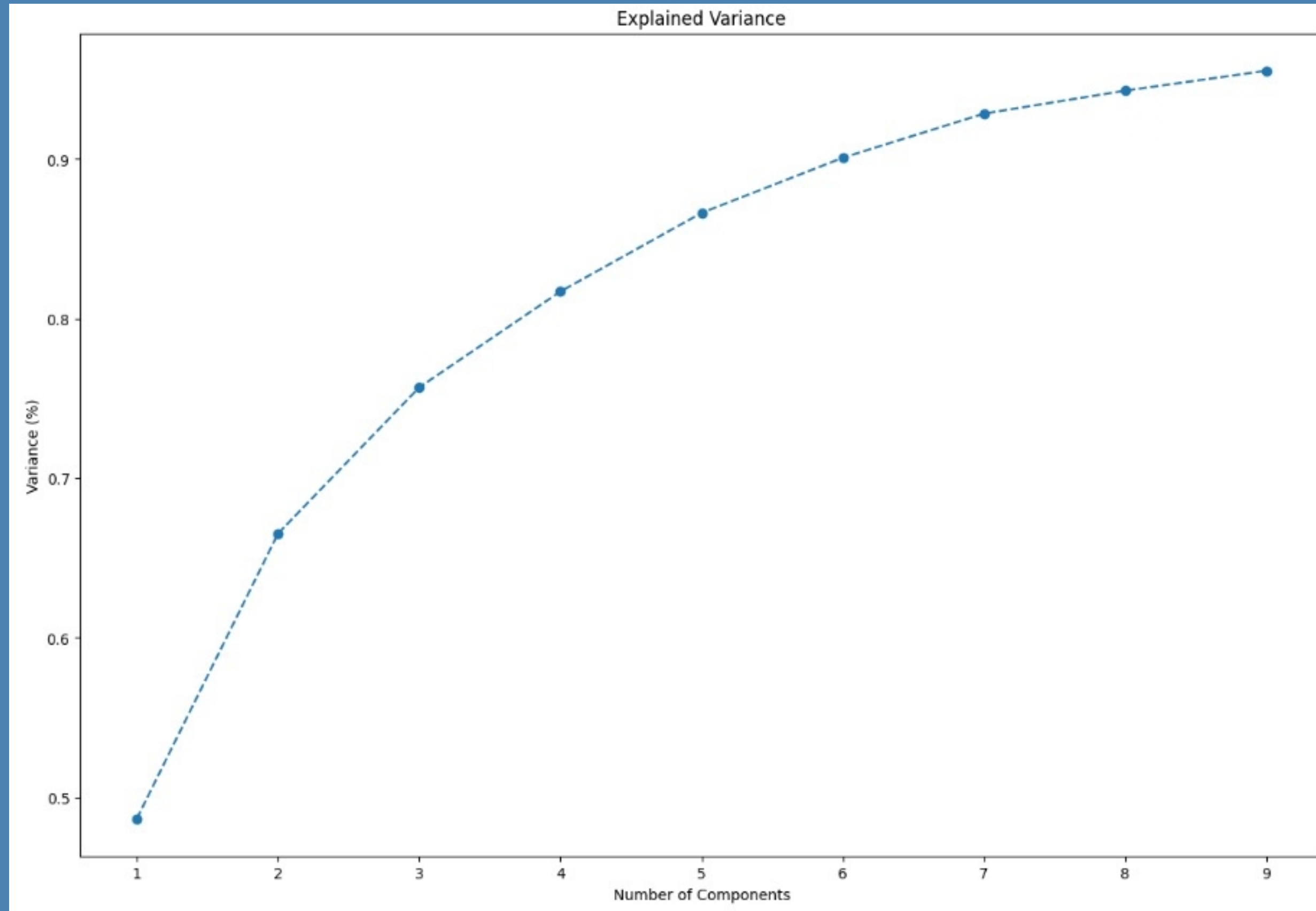
**Index Terms**- Parkinson Disease, Early Diagnosis, Classification, Machine Learning, Speech Data, Pattern Matching, SVM.

vowels /i/, /u/, and /a/ , and various ratios of these vowel formants. The reason for using such acoustic analysis is that the F1 and F2 of these vowels reflect the movements of the tongue, lips, and jaw [5], [7].

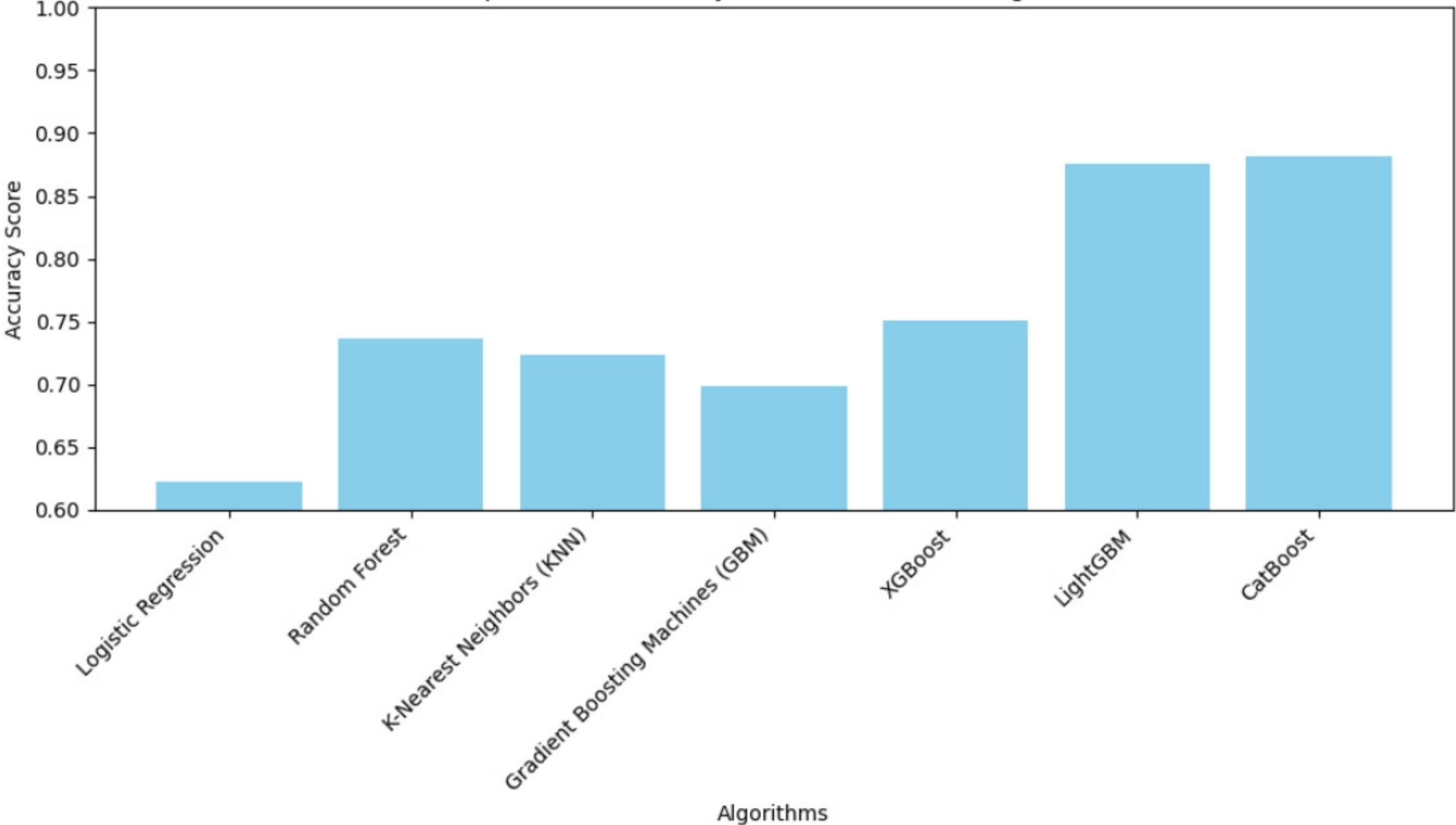
Specifically, F2 increases and F1 decreases in formant frequency as the tongue moves forward (as in the case of the vowel /i/), and, respectively, F2 decreases and F1 increases in frequency when the tongue moves backwards (as in the vowel /u/). Also, F1 formant frequency decreases when the tongue goes up (e.g., for the vowels /i/ and /u/) and increases as the tongue goes down, along with the jaw (e.g., for the vowel /a/). Furthermore, Both F1 and F2 decrease when the lips are rounded (e.g., for the vowel /u/) and increase when the lips are unrounded or detracted (as in the vowels /i/ and /a/).

In PD the movements of the speech articulators (lips, tongue, jaw) are restricted in range (hypokinetic), and as a

# VARIANCE PLOT

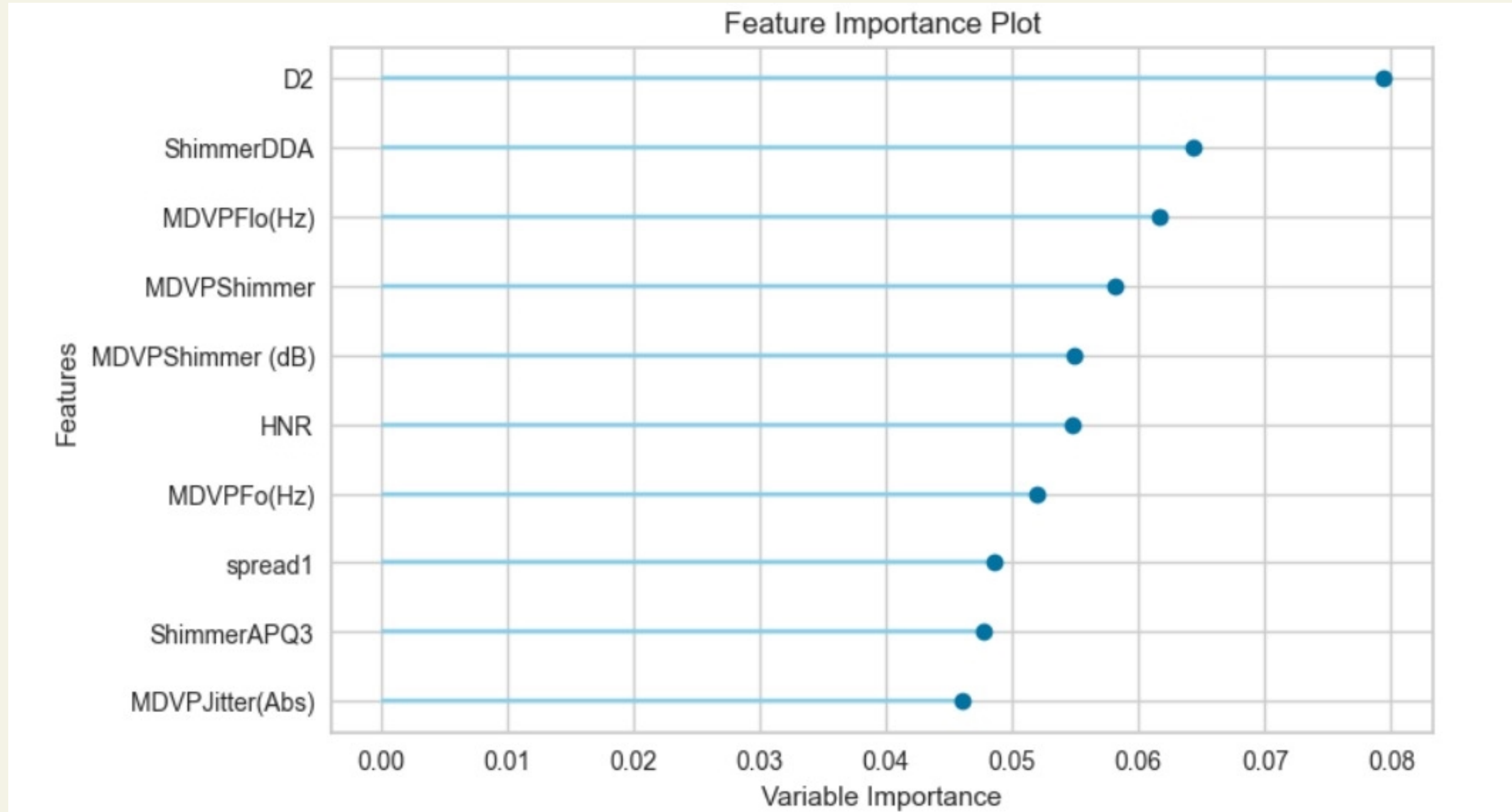


Comparison of Accuracy Scores for Different Algorithms

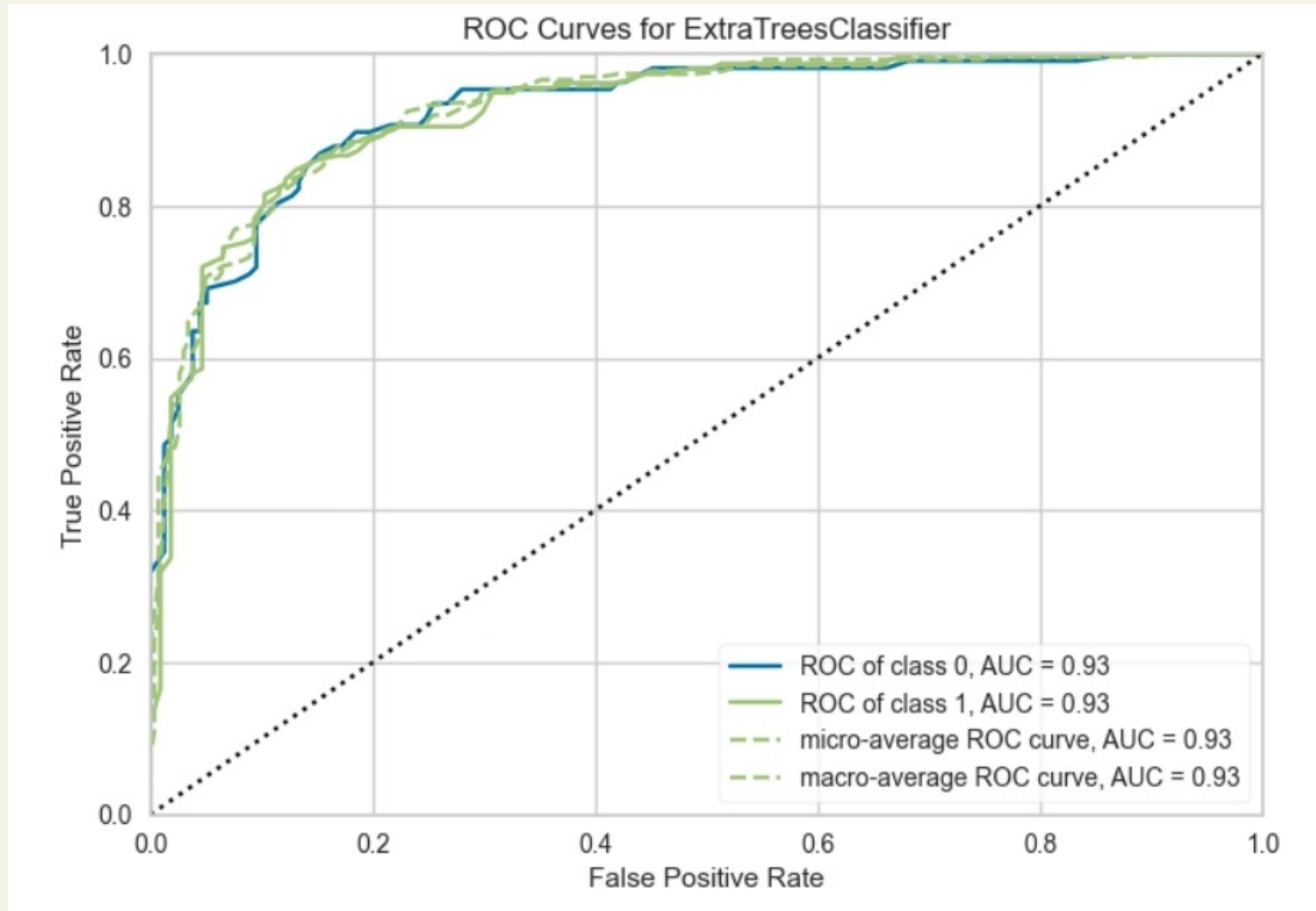


	<b>Model</b>	<b>Accuracy</b>	<b>AUC</b>	<b>Recall</b>	<b>Prec.</b>	<b>F1</b>	<b>Kappa</b>	<b>MCC</b>
<b>et</b>	Extra Trees Classifier	0.8539	0.9307	0.8640	0.8908	0.8760	0.6980	0.7012
<b>rf</b>	Random Forest Classifier	0.8327	0.9227	0.8453	0.8744	0.8577	0.6548	0.6595
<b>lightgbm</b>	Light Gradient Boosting Machine	0.8231	0.9119	0.8396	0.8629	0.8501	0.6342	0.6367
<b>xgboost</b>	Extreme Gradient Boosting	0.8229	0.9140	0.8505	0.8545	0.8515	0.6321	0.6340
<b>gbc</b>	Gradient Boosting Classifier	0.8085	0.8971	0.8209	0.8567	0.8365	0.6054	0.6100
<b>ada</b>	Ada Boost Classifier	0.7889	0.8576	0.7962	0.8445	0.8176	0.5672	0.5717
<b>dt</b>	Decision Tree Classifier	0.7694	0.7653	0.7878	0.8241	0.8037	0.5240	0.5282
<b>lda</b>	Linear Discriminant Analysis	0.7316	0.7866	0.7038	0.8268	0.7588	0.4598	0.4697
<b>ridge</b>	Ridge Classifier	0.6813	0.7569	0.6708	0.7691	0.7157	0.3565	0.3623
<b>lr</b>	Logistic Regression	0.6765	0.7543	0.6571	0.7686	0.7077	0.3502	0.3566
<b>knn</b>	K Neighbors Classifier	0.6608	0.7321	0.6870	0.7274	0.7042	0.3063	0.3093
<b>svm</b>	SVM - Linear Kernel	0.5353	0.6266	0.4446	0.6354	0.5003	0.1134	0.1106
<b>nb</b>	Naive Bayes	0.5276	0.6799	0.2637	0.8354	0.3960	0.1574	0.2307
<b>qda</b>	Quadratic Discriminant Analysis	0.4026	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
<b>dummy</b>	Dummy Classifier	0.4026	0.5000	0.0000	0.0000	0.0000	0.0000	0.0000

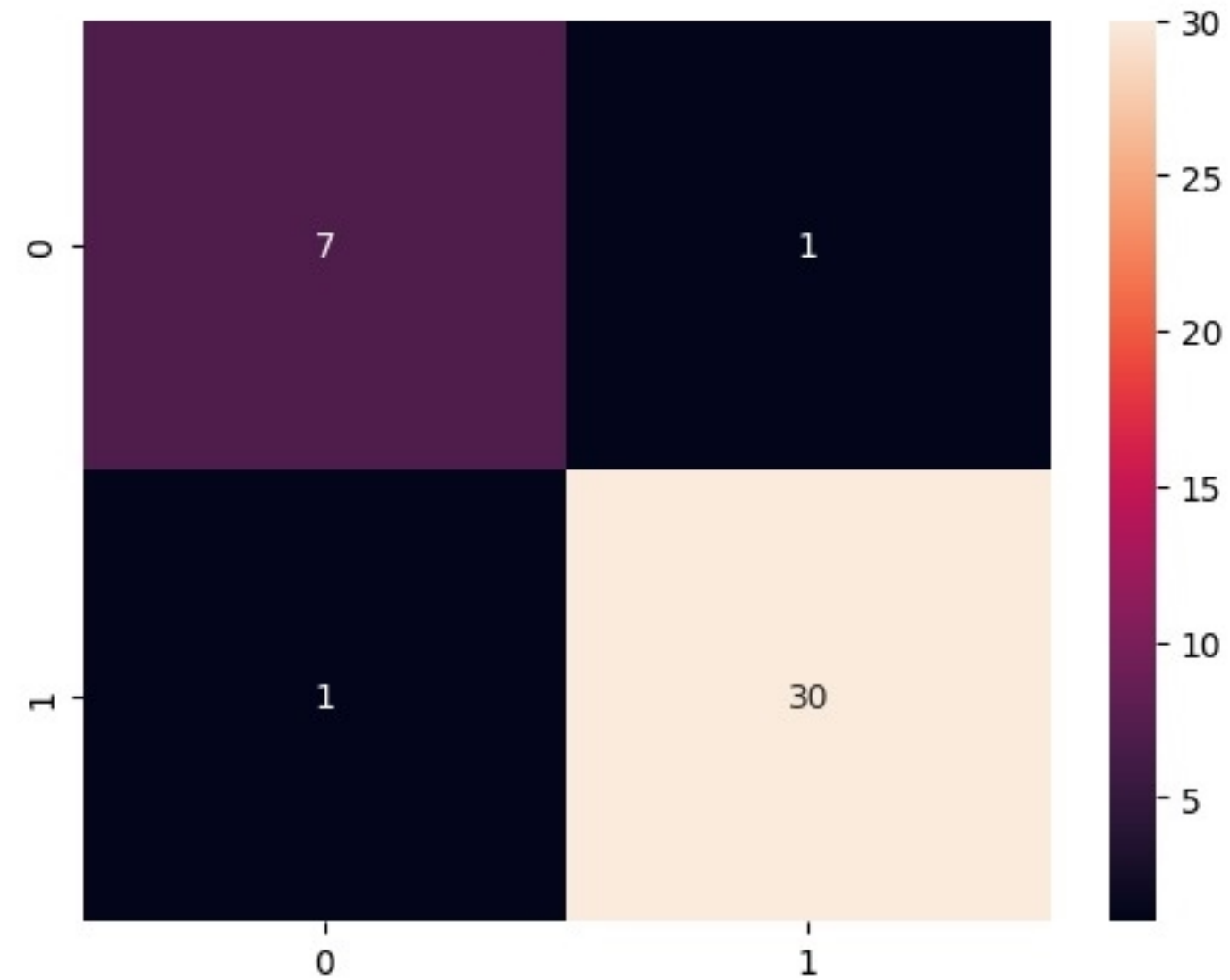
# EXTRA TREES



# EXTRA TREES

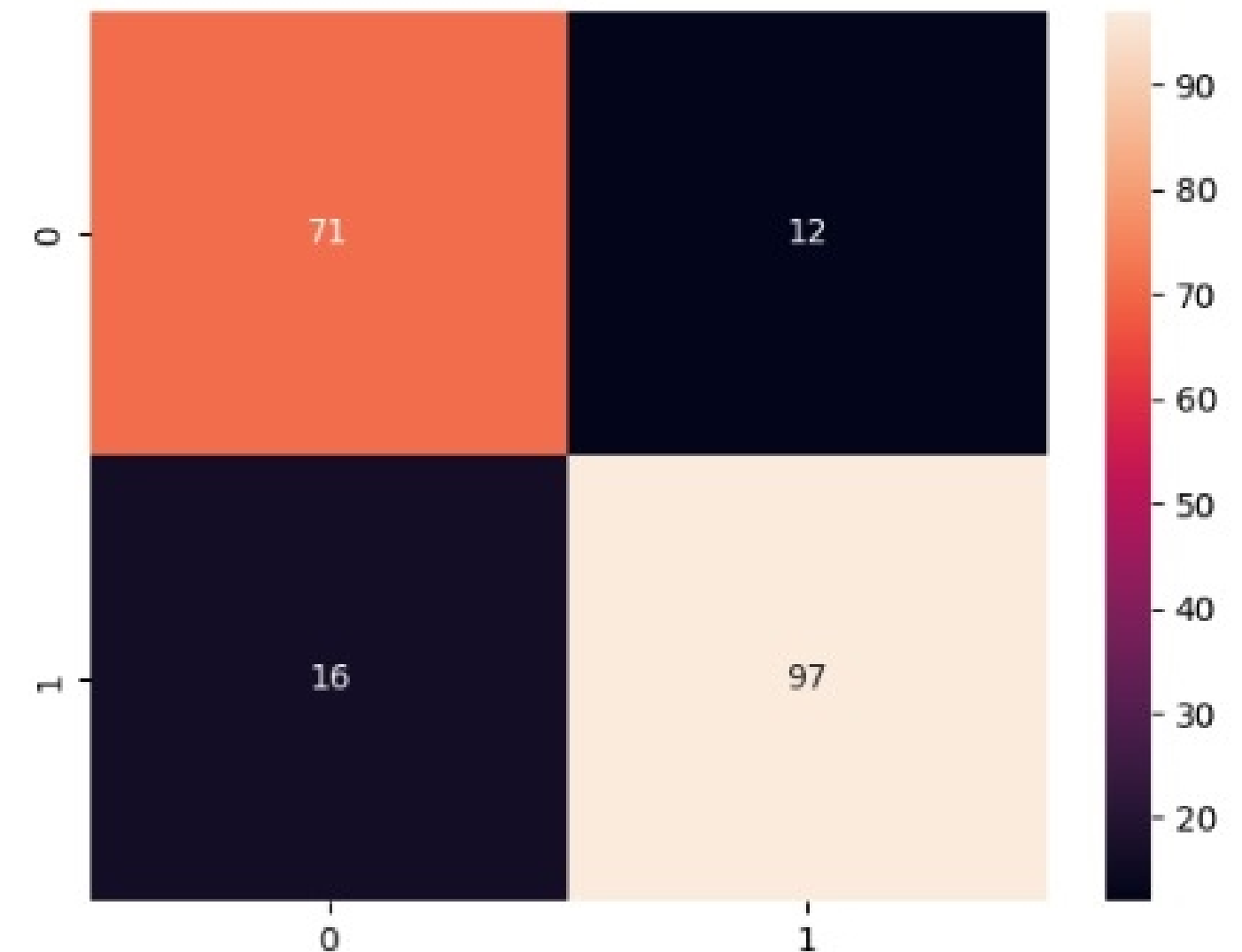


Extra Trees Evaluation for English data:



	precision	recall	f1-score	support
0.0	0.88	0.88	0.88	8
1.0	0.97	0.97	0.97	31
accuracy			0.95	39
macro avg	0.92	0.92	0.92	39
weighted avg	0.95	0.95	0.95	39

Extra Trees Evaluation for Merged data:



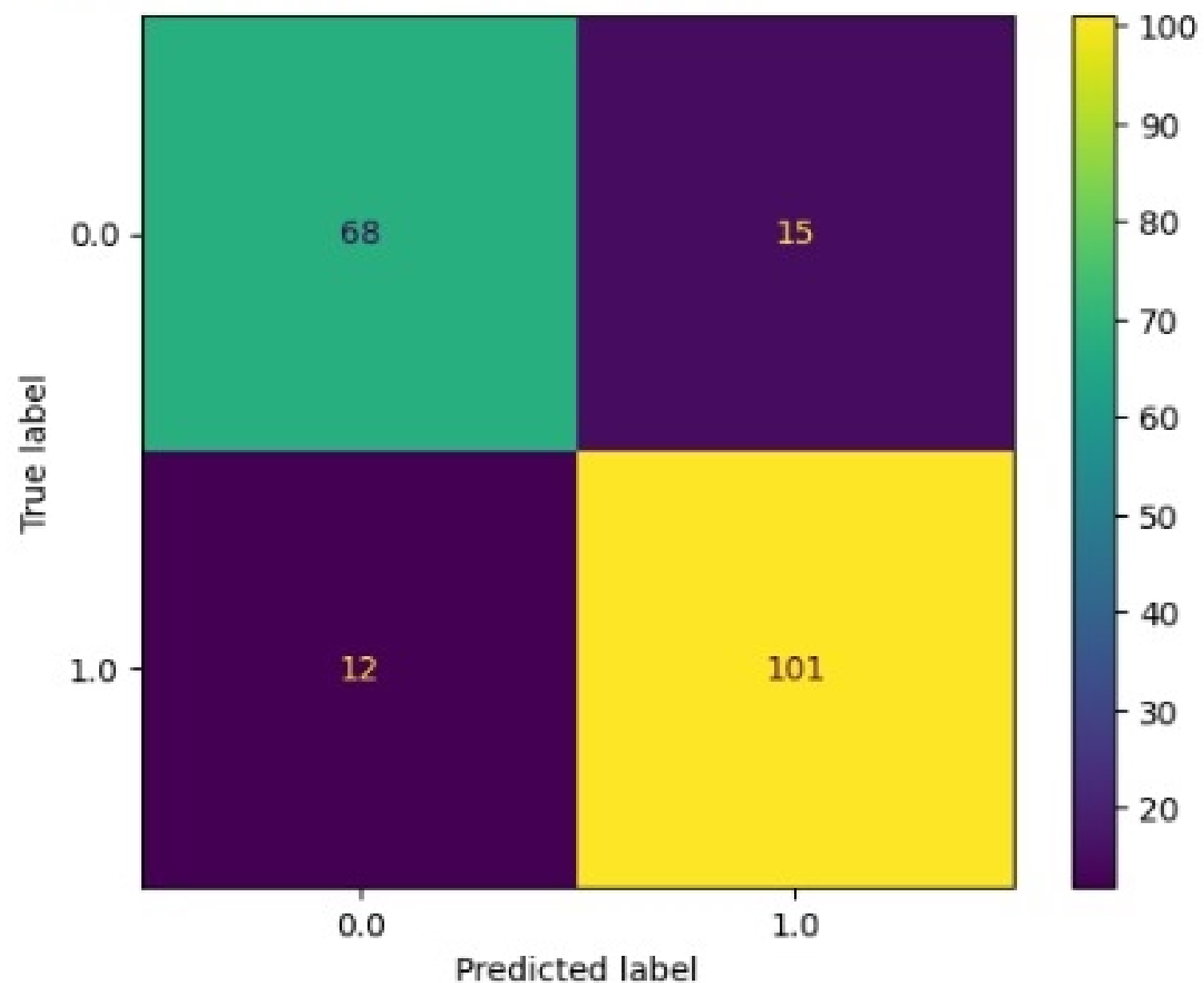
	precision	recall	f1-score	support
0.0	0.82	0.86	0.84	83
1.0	0.89	0.86	0.87	113
accuracy			0.86	196
macro avg	0.85	0.86	0.85	196
weighted avg	0.86	0.86	0.86	196

Mean Cross-Validation Accuracy: 0.8996682681308625  
 Test Accuracy: 0.8673469387755102



# STACKING CLASSIFIER

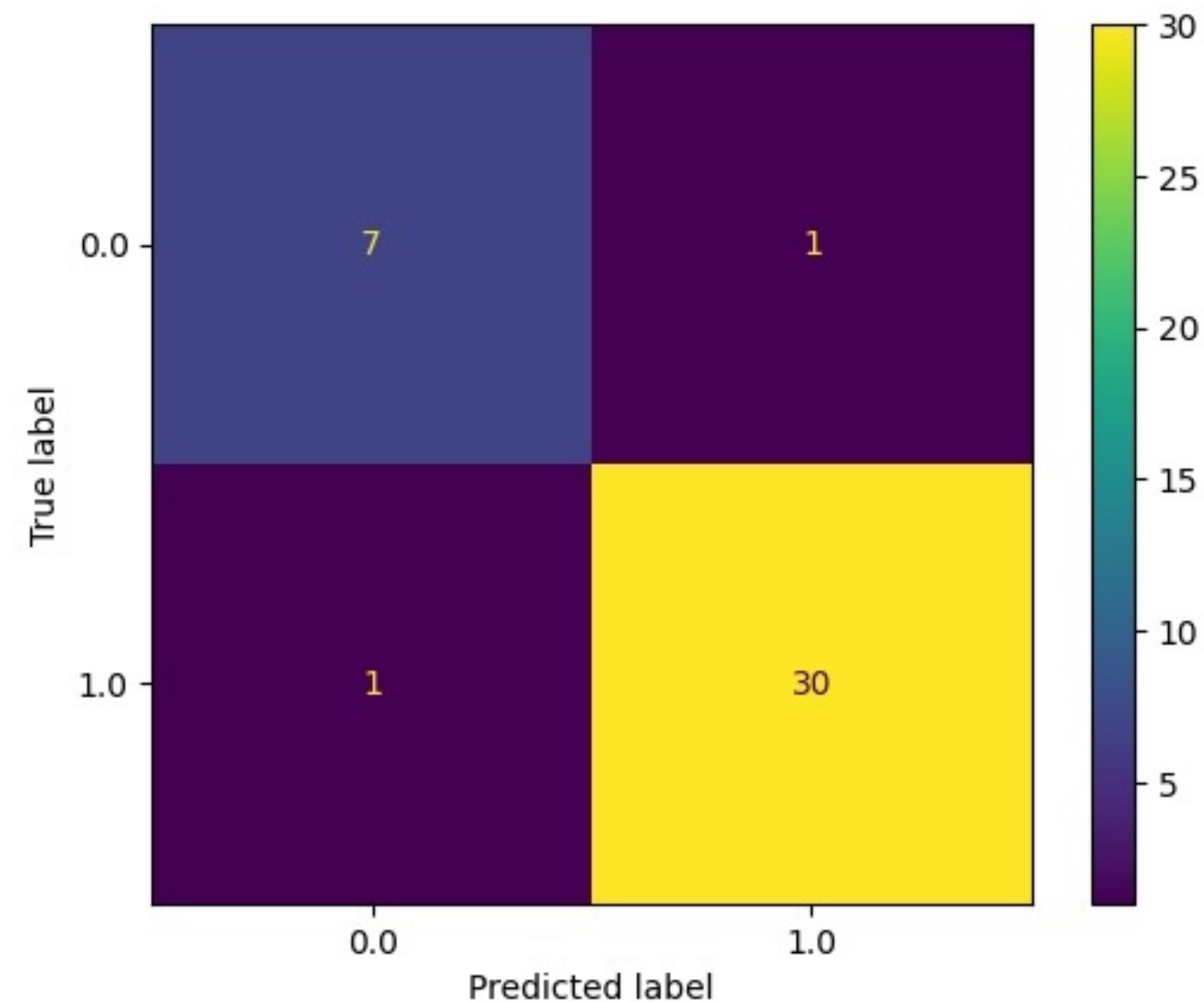
Train on Merged Data, Test on Merged Data:



Accuracy: 0.8622448979591837  
Precision: 0.8619282195636875  
Recall: 0.8622448979591837  
F1 Score: 0.8618795389669786

Stacking Classifier Evaluation:

Train on English Data, Test on English Data:

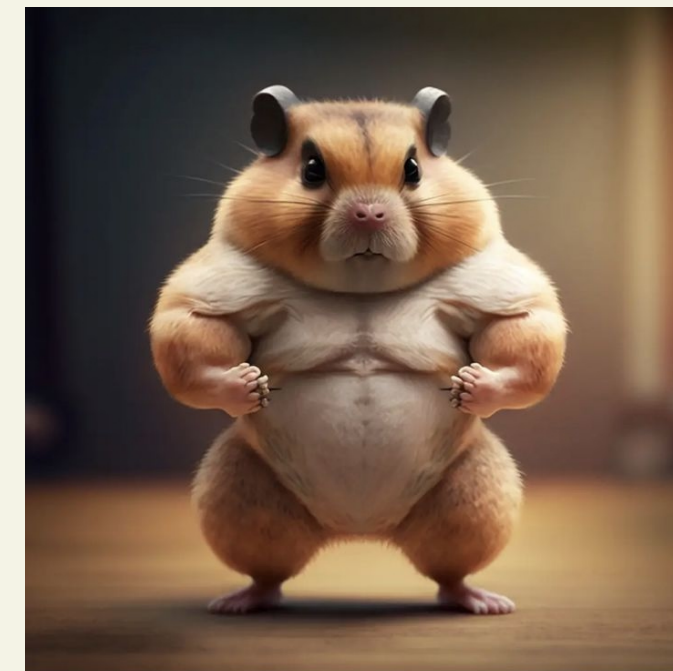
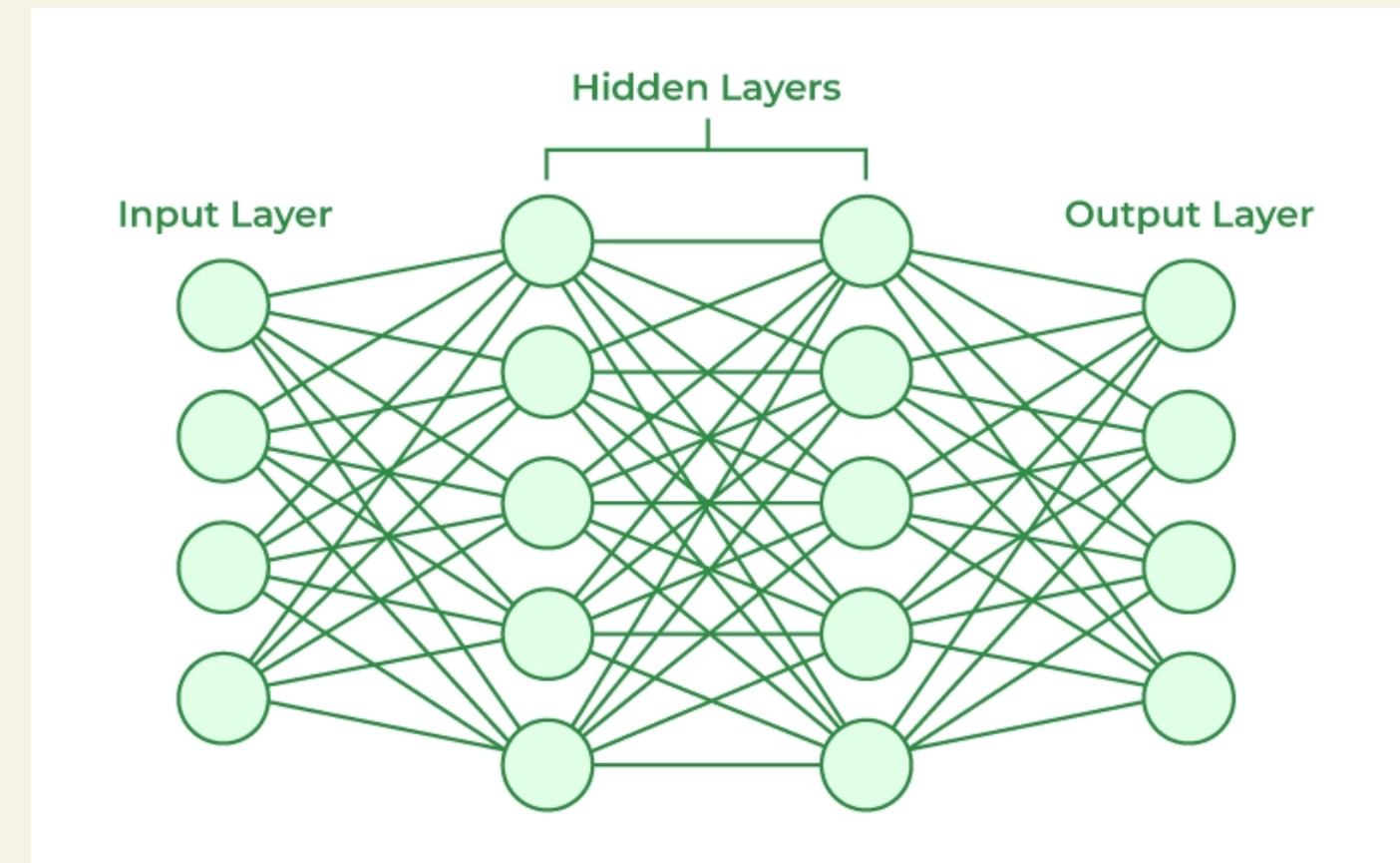


Accuracy: 0.9487179487179487  
Precision: 0.9487179487179487  
Recall: 0.9487179487179487  
F1 Score: 0.9487179487179487

# WE ALSO TRAINED A DNN

- Epochs Variation: 1000,5000,10000
- Hidden Layers: 2,3,4

```
Accuracy on test data: 72.45%  
Confusion Matrix:  
[[50 29]  
 [25 92]  
Precision: 0.7603305785123967  
Recall: 0.7863247863247863  
F1 Score: 0.773109243697479
```



# WHERE DOES THIS LEAD US?

v Accuracy/ Model ->	Anglo-German	Anglo-Italian
Merge Train Merge Test	~80%	<b>86.2%</b>
Single Train Single Test	~85%	<b>94.8%</b>

# CHALLENGES & FUTURE DEVELOPMENT



LESS DATA FOR ENGLISH LANGUAGE

- NORMALIZATION BLACKBOXES

LANGUAGES OF DIFFERENT ORIGINS

- OBTAIN MORE DATA
- TRAIN BETTER NEURAL NETWORK
- MAKE A 2+ LANGUAGE MODEL WITH  $>85\%$  ACCURACY



# TEAM

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MEHROTRA



PRERIT  
RATHI

PRATEEK  
RANA

# References

<https://archive.ics.uci.edu/dataset/470/parkinson+s+disease+classification> <https://archive.ics.uci.edu/dataset/174/parkinsons>  
<https://archive.ics.uci.edu/dataset/189/parkinsons+telemonitoring>  
<https://archive.ics.uci.edu/dataset/301/parkinson+speech+dataset+with+multiple+types+of+sound+recordings>  
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