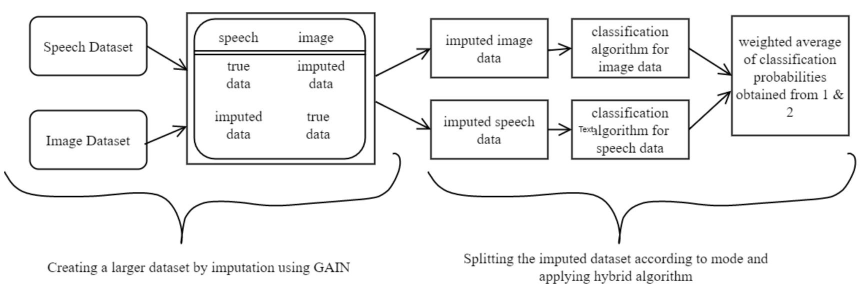
Parkinson’s Disease Detection using Imputed Multimodal Datasets

Parkinson's disease is a progressive nervous system disorder that affects movement, often including tremors. Work has been done on developing systems for early-stage detection of Parkinson’s disease. During our literature survey we observed that there are many available datasets, but most are small (< 200 subjects), and often have multiple samples from the same subject. Either the current state-of-the-art models assume the source of the multi-modality to be the same, or they lack deployability in low-income areas, because of their dependence on means of data-collection which require expensive equipment [5,6]. In our goal to build a more generalizable hybrid model, we decided to tackle this problem. We utilize information from 3 datasets available in the public domain, namely- Multiple Sound Recordings (MSR) Dataset [1], Sri Lanka (SL) Dataset [2], and Hand Drawing (HD) Dataset [3]. Note that we specifically make use of this data with the goal of usability- these features can be collected from participants of any study by relatively inexpensive equipment, like a drawing tablet and a recording tool. Note that the available data has been taken from different sources and therefore cannot be merged without introducing missing values. Thus, we impute these 3 datasets together using a Generative Adversarial Imputation Network (GAIN) [4] to create a new, larger dataset with more features and samples. We test several classification algorithms on the non-imputed, but smaller datasets individually, and on the imputed dataset. Consistently a higher accuracy post-imputation was observed. Even when we consider imputation, we observe that imputing 2 speech + 1 image dataset leads to a marginal increase in accuracy compared to the 1 speech + 1 image dataset case.



10 fold cross validation, mean validation accuracy		
Model	**MSR-HD**	**MSR+SL-HD**
Logistic Regression	0.902	0.909
Gaussian Naive Bayes	0.68	0.548
k-NN, k=4	0.842	0.839
k-NN, k=6	0.843	0.849
SVM with poly kernel	0.847	0.88
SVM with rbf kernel	0.82	0.819
Decision Tree	0.874	0.784
Random Forest	0.908	0.884
AdaBoost	0.923	0.874
GradientBoost	0.901	0.894
xgboost	0.918	0.924
Multi Layer Perceptron	0.892	0.904

We also propose a hybrid algorithm to fully utilize the different kinds of structural information provided by images and sound features. We train a MLP on the obtained imputed speech data and a CNN on the imputed image data. Finally, we take a weighted average of the classification probabilities obtained from the 2 classifiers and make our final prediction. We were able to get an accuracy of 93.5% with our hybrid algorithm on the imputed dataset. This technique will be helpful for present-day machine learning architectures, especially in fields like medical science where we do not have access to large amounts of data and the available data has been taken from different sources.

References: [1] B. E. Sakar, M. E. Isenkul, C. O. Sakar, A. Sertbas, F. Gurgen, S. Delil, H. Apaydin, and O. Kursun. Collection and analysis of a Parkinson speech dataset with multiple types of sound recordings. IEEE Journal of Biomedical and Health Informatics, 17(4):828–834, 2013

[2] Vaseekaran Varatharajah. Parkinson’s Voice Data - Sri Lanka

[3] Poonam Zham, Dinesh K. Kumar, Peter Dabnichki, Sridhar Poosapadi Arjunan, and Sanjay Raghav. Distinguishing different stages of parkinson’s disease using composite index of speed and pen-pressure of sketching a spiral. Frontiers in Neurology, 8:435, 2017.

[4] Jinsung Yoon, James Jordon, Mihaela van der Schaar, "GAIN: Missing Data Imputation using Generative Adversarial Nets," International Conference on Machine Learning (ICML), 2018.

[5] Bowman FD, Drake DF and Huddleston DE (2016) Multimodal Imaging Signatures of Parkinson's Disease. Front. Neurosci. 10:131. doi: 10.3389/fnins.2016.00131

[6] J. C. Vásquez-Correa et al., "Multi-view representation learning via gcca for multimodal analysis of Parkinson's disease," 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2017, pp. 2966-2970, doi: 10.1109/ICASSP.2017.7952700.